The Structure of Support: Exploring How Social Networks Influence the Physical and Mental Health of U.S. Adults

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Dissertation submitted in partial fulfillment of
the requirements for the degree of Doctor
of Philosophy in the Department of
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ABSTRACT

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Abstract

An extensive body of research documents the strong influence of social relationships, social support, social integration and social networks on well-being. Nonetheless, conceptual clarity remains elusive and these terms are often used interchangeably, precluding confident conclusions and hindering cross-study comparisons. Guided by social network analysis, the social convoy model and the life course framework, I measure social network structure and composition through the use of typologies. I then examine the influences of social network structure and composition on an array of health indicators, including self-rated health, psychological distress and self-esteem.

This study uses data from the Americans' Changing Lives Survey, a nationally representative longitudinal panel survey of adults aged 25+ interviewed in 1986, 1989, 1994 and 2001/2002. I use hierarchical cluster analysis to create social network typologies from data on respondent reports of close confidants and develop two typologies, one for social network structure and the other for social network composition. In cross-sectional analyses, I use logistic regression and Poisson regression to examine the associations between these two social network typologies and poor/fair self-rated health, high self-esteem, and counts of depressive symptoms. I also perform two sets of longitudinal analyses to determine the predictive utility of network structure and composition for health. First, I use OLS regression to examine whether the social network typologies predict residual change scores for self-rated health, psychological

distress, and self-esteem both 3 and 8 years after the baseline survey. Second, I use autoregressive cross-lagged models within a structural equation framework to disentangle the effects of social causation and social selection on the relationship between social network structure and the three indicators of health mentioned above.

The typologies representing social network structure and composition are strongly related to important social and demographic factors. In addition, there are strong and significant cross-sectional associations between these typologies and indicators of mental health, although their association with self-rated health is weak at best. The typologies are highly predictive of changes in mental health across waves, although again, they are not strongly related to changes in self-rated health. Lastly, this dissertation finds strong support for both social causation and selection processes at work in the relationships between social network structure and self-rated health and psychological distress. Support social selection, but not social causation, was found in regards to self-esteem.

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1. Introduction

Attempting to understand the importance of social life for individual and population health and well-being has a long history, originating with Durkheim (1897). In Suicide, Durkheim demonstrated that taking one's own life was fundamentally a social issue, with country-level suicide rates associated with levels of social integration and coherence within society. Cassel (1976) and Cobb (1976) highlighted the importance of supportive social relationships in protecting health across the life course, as individuals pass through life stages, transitions, and crises. Indeed, social disconnectedness and isolation have been associated with poorer physical and mental health, with the health risk comparable in magnitude to the risk of smoking cigarettes (House 2001; Cornwell and Waite 2009). Community-based epidemiological studies have illustrated, time and again, that larger social networks are protective against all-cause, cardiovascular and cancer mortality (Berkman and Syme 1979; House, Robbins and Metzner 1982; Schoenbach et al. 1986; Orth-Gomér and Johnson 1987; Seeman et al. 1987; Pinquart and Duberstein 2010). More recent research suggests that the relationship between health and social networks may be reciprocal; while social networks affect health, health is also important in shaping the composition and structure of social networks, as well as individuals' position within networks (Cornwell 2009a; Cornwell 2009b; Cornwell and Waite 2009; Haas, Schaefer and Kornienko 2010).

Supportive social relationships have been measured in multiple ways, with terms such as social relationships, social network, social support and social integration often used interchangeably. The social convoy model, as proposed by Kahn and Antonucci (1980), places emphasis on the *structure* of social relationships as important to health and well-being as people age. This dissertation attempts to bridge the gap between the health literature and developments in social network analysis by using personal network data, namely respondent reports of close confidants, to measure social convoys.

Exploratory in nature, the first analytical section of this dissertation uses hierarchical cluster analysis to create social convoy typologies representing network structure and composition. Building off findings from the first chapter, I test the associations between these social convoy types and an array of health indicators, including self-rated health, psychological distress and self-esteem. Then, I examine age, gender and race as potential moderators in the association between the social convoy types and these health indicators. Next, using residual change score analysis, I determine whether the social convoy types predict *changes* in self-rated health, psychological distress and self-esteem across time, from 1986 to 1994. Lastly, in an effort to further tease out issues of social causation and social selection, I use autoregressive cross-lagged models within a structural equation framework to ascertain the extent to which social convoys affect health and health affects social convoys over time.

Chapter 2 introduces the theoretical background for this study, including social network analysis, the social convoy model (Kahn and Antonucci 1980), and the life course perspective. In addition, Chapter 2 reviews the prior literature on the measurement of social convoys (networks) and relevant findings regarding the link between social network and various measures of health and well-being.

Chapter 3 introduces the data and methods I will be using to develop social network typologies and to examine their relationships to self-rated health, psychological distress and self-esteem at baseline and over time.

Chapter 4 uses hierarchical cluster analysis to develop social network typologies from data on respondent-reported close confidants.

Chapter 5 contains both cross-sectional and longitudinal analyses. For the cross-sectional analyses, I use logistic regression and Poisson regression to examine the associations between social convoy typologies and poor/fair self-rated health, high self-esteem and counts of depressive symptoms at baseline. For the longitudinal analyses, I use OLS regression to examine the effect of social convoy types (as measured at baseline in 1986) on residual change scores for self-rated health, psychological distress and self-esteem measured using data from the second (1989) and third (1994) waves of the survey.

Chapter 6 uses autoregressive cross-lagged models within a structural equation framework to ascertain how social convoys affect mental and physical health over time, and how health affects the structure and composition of social convoys over time. This chapter helps to shed light on the whether social causation, social selection, or both processes are at work in the connection between social convoys/networks and health measures.

Chapter 7 concludes with a review of relevant findings, strengths and limitations of the study and directions for future research.

2. Theory and Literature Review

Past research has clearly documented the health benefit of supportive social relationships, social networks, and social support (House, Landis and Umberson 1988). A large bulk of this literature has focused on the importance of social support to individual well-being throughout the life course, for both its direct and indirect contributions (e.g., the ability of social support to moderate the effects of stress). Social networks, also termed social convoys here, are the structures through which social support is exchanged. This dissertation focuses on understanding the importance of social convoys for the health and well-being of U.S. adults. In it, I examine the dynamic, reciprocal relationships between social convoys, as measured by respondent reports of close confidants, and mental and physical health among a nationally representative of U.S. adults. In this chapter, I introduce three theoretical perspectives that guided the development of this dissertation research: social network analysis, the social convoy model and the life course perspective Then, I review the literature on the measurement of social convoys and their relationships with various measures of mental and physical health. I conclude with a discussion of how this dissertation builds and improves on the existing literature in this area.

2.1 Using Social Network Analysis

The terms social relationships, social networks and social support have often been used interchangeably, although they refer to separate, distinct concepts. Social relationships are the presence (or absence) of certain social ties or bonds. Thus, marital status or parental status would be indicators of the presence (or absence) of certain social relationships. The presence of social relationships is the foundation for the formation of social network structure. Social network analysis is a visual field of study, where each actor is represented by a node and each transaction or exchange represented by a link. Thus, nodes and links combine to form network structure, through which various social resources flow. Social support has been described as the actual and perceived resources available to an individual from their network members (Luke and Harris 2007). Social support represents social functions provided through membership in a network, the exchange of which links people together.

Social network concepts can be useful in describing patterns of relationships that are not easily explained by more traditional kinship relations. Network analysis allows for the examination of all kinds of potential ties rather than restricting it to traditional expectations of the kinds of people and types of relationships likely to constitute a person's social world (Berkman 1984). Network analysis is a structural approach dealing with relational data, focusing on connections and links between actors. This approach does not concentrate on the attributes of people, but on the social linkages between people and the characteristics of the social network itself (Wasserman and Faust 1994). Structural attributes describe the structure or relational information of the network and include measures of network size (the number of members in a network) and density (the extent to which members are connected to each other). Compositional attributes describe the actors within the network and may include measures of homogeneity (the extent to which members are similar to each other in terms of social and demographic factors) and boundedness (the degree to which membership is based on kinship, geographic location, etc.) (Berkman et al. 2000).

Ideally, social network researchers would collect data on *all* actors and their ties to other actors within a bounded community where prior identification of all actors is required, what is commonly referred to as a full or *global social network*. This type of data can provide researchers with rich information on individuals' local network characteristics and global network position (Haas et al. 2010). Unfortunately, this type of data collection is time consuming, resource expensive and requires study populations contained within a well-defined, bounded environment. Thus, it is not surprising that much of the available global social network data has been collected primarily from adolescents, a relatively captive population within a naturally bounded environment (i.e., schools). Research using data from sources such as the National Longitudinal Study of Adolescent Health (Add Health) has provided a solid foundation of evidence for the strong influences of network position on cigarette smoking, substance use, delinquency and other risk-taking behaviors (Luke and Harris 2007). The only global network data on adults the author is aware of is that collected by Schafer (2012) from older residents in a continuing care retirement facility.

Much of our knowledge pertaining to health, aging and social relationships has come from large-scale, observational surveys, few of which have measured ego-centered networks. An ego-centered network consists of a focal actor or respondent (termed *ego),* a set of actors who have ties to ego (ego's *alters),* and measurements of the ties from ego to his/her alters and of ties between alters. Such data are referred to as *personal network data* or *local networks* (Wasserman and Faust 1994). Local network measures, such as network size or density, are informative because they determine access to social support, information, material resources and aid acquired directly from individuals' social contacts (Haas et al. 2012). Data sources such as the General Social Survey (GSS) and National Social Life, Health and Aging Project (NSHAP) collect data on local networks, although to-date both sources of publicly available data are cross-sectional. The data used in this dissertation comes from the Americans' Changing Lives (ACL) study, which is a longitudinal panel survey and includes a limited assessment of personal network measures derived from respondent reports of close confidants.

2.2 The Social Convoy Model

The above-mentioned personal social network is similar to a concept called the social convoy. The social convoy was introduced by Kahn and Antonucci (1980) to describe the structure in which social support is given and received. A person's social convoy consists of individuals whom they rely on and/or who rely on them for support. The concept of the social convoy is focused around social roles, or positions within the social structure (husband-wife, parent-child, employer-employee, friend-friend) to which are attached sets of reciprocal expectations and obligations (Thoits 2011). It is through social roles that individuals form strong bonds and attachments throughout their lives and it is these attachments that make up a person's social convoy.

In the view of Kahn and Antonucci (1980), the social convoy is important for well-being because of its role in the provision of social support. Membership in a social convoy is dependent on individuals being important to a focal person through the giving and receiving of social support, as well as other forms of assistance and resources. A person may have a large number of social convoy members, but members may differ in their importance to the focal person. The social convoy may be composed of important relationships that are tied to non-intimate social roles and may change with changes in social roles (i.e., co-workers); important relationships that are somewhat role-dependent, and may (or may not) change over time; and close, intimate relationships that are stable over time and not likely to change due to changes in social roles, geographic proximity or social contact (Kahn and Antonucci 1980). This inner-most circle is usually composed of close confidants, perhaps a spouse, a partner, or close friends or family members.

The social convoy model makes a number of important contributions to the health literature. First, it helps to clarify the relationships between social roles, social relationships, social support and social networks (i.e., convoys). Second, social convoys are seen as an essential area of research because they are the structure through which social support is given and received. Although I believe network structures may be important for health because of their direct effects, the social convoy models emphasizes the indirect effects of social convoys, namely as vessels for the provision social support. In emphasizing the role of social support on health, this model also calls for a substantive definition of social support, defined as interpersonal transactions that can be characterized by affect, affirmation and/or aid. Lastly, the social convoy model integrates tenets of the life course perspective, calling for a dynamic view of social convoys and comparing network properties of individuals as they age (Antonucci and Akiyama 1987; Kahn and Antonucci 1980).

This dissertation uses personal network data from the Americans' Changing Lives (ACL), a nationally representative, longitudinal survey. Through the use of respondent reports of close confidants, this research ensures that the measurement of social convoys fulfills the above-mentioned substantive definition of social support. In addition, using information derived from personal social networks is essential because kinship or the mere presence or absence of certain social relationships may be incomplete for the purpose of measuring social convoys (Kahn and Antonucci 1980). In relying on the mere presence or absence of certain social ties, certain unsupportive social ties may be included, while more supportive ties are excluded. This is confirmed by the data used in this dissertation. Among all married respondents, only half reported their spouse as a close confidant. Among all parents, only 1/5 reported a child as a close confidant, and among those whose parents were still alive, only 15% reported a parent as a close confidant.

2.3 The Life Course Framework

While it is believed that social networks influence health through the provision of social support, in addition to social engagement, social influence and access to resources, aid and information (Berkman et al. 2000), no specific constellation of social relationships is optimal for well-being as individuals' age (Adams and Blieszner 1995). The size and composition of social convoys change with age, as individuals transition into major social roles (e.g., that of spouse, parent, worker) during young adulthood and transition out of major social roles later in life (e.g., retirement, widowhood, divorce, etc.). Indeed, in a review of the literature on social networks and aging, Adams and Blieszner (1995) argue that the mere existence of social relationships does not indicate that a person is aging well, as not all personal relationships are positive ones. The optimal level of social embeddedness for individuals depends on their situational contexts, as well as personal needs and abilities, and thus very likely varies over time. In understanding the importance of social convoys for health and well-being, it is essential to take into account the life course perspective.

Human development and aging are life-long processes, extending from birth until death (Elder, Johnson and Crosnoe 2003). The life course perspective promotes the understanding of development and aging across changing social contexts (Elder et al. 2003) by focusing on the importance of time, both biographical and historical (George 1999). The life-course perspective is composed of four central tenets. First, it advocates taking a long view of individual lives through examining the timing, duration and sequencing of life events, transitions between states and trajectories over time (biographical time). This is essential because the effect and meaning of the same life event can differ depending on when it occurs in the life course (Elder et al. 2003).

Secondly, this perspective focuses on how individual life course trajectories are embedded in and affected by the historical, political, social and economic context (historical time) (George 1999; Elder 1994). While not all life course research examines cohort and period effects, it is essential that researchers interpret their findings in light of the historical context in which the data was collected. Third, life course researchers acknowledge the importance of human agency and social constraints in decision making. This paradigm views individuals as 'planful', making choices and decisions within the constraints of a particular situation or context (Elder, George and Shanahan 1996). Thus, life course theory favors a constructionist view, whereby individuals are seen as distinctly shaping their own future life course within the constraints of existing social structures.

Lastly, this perspective focuses on 'linked lives' -- namely, how individuals are embedded in and affected by their social networks, formed through the institutions of the family, school, and work (George 1999). Because lives are lived interdependently, transitions in the life of one network member may cause transitions in the lives of other network members (Elder et al. 2003). In addition, the initiation of a new social relationship or end of an old one may also have important implications for life transitions, behavior and health. Elder (1994:6) states, "No principle of life course study is more central than the notion of interdependent lives". Thus, issues of the life course cannot be studied in isolation, but should take into account peoples' degrees of social embeddedness across the life span.

In sum, life course scholars are interested in uncovering the dynamic interplay between human agency, social structure and social context, and the life course paradigm has made these elements more salient dimensions of both theory and analysis. Attributes of a social convoy, (such as size, homogeneity and density) are affected by an individual's social location, and may change over biographical time, as people enter and exit social roles, change living arrangements and/or move their geographic location (Adams and Blieszner 1995). This dissertation research is guided by the life course perspective in a number of ways. First, this research is concerned with "linked lives" and how social network members can influence the mental and physical health of other network members. Second, this research focuses on the dynamic, reciprocal relationships between social networks and mental and physical health as people age. Third, while all findings will be interpreted based on the historical time period in which the data were collected, I will argue that, while Americans' social convoys may have changed over time, the linkages between convoys and health should be just as true today as when the data were collected.

2.4 Measuring Social Convoys

In trying to understand the social network-health connection, researchers have differed in their measurement of social networks (or convoys) in three primary ways. First, the variables used to measure social networks have differed across studies. Second, while some researchers have used *variable-centered* approaches, more recent endeavors have used what will be referred to as *person-centered* approaches. Third, the variables examined as potential moderators in the social network-health connection have varied across studies.

2.4.1 Different Variables

Previous large-scale, observational studies used different criterion variables in measuring social networks (convoys). While many studies used marital status, number of children, contact with children, friends, and neighbors, and church and group membership (Litwin 1997; Litwin 1998; Litwin and Landau 2000; Litwin 2001; Fiori, Antonucci and Cortina 2006; Litwin and Shiovitz-Ezra 2006), still others used a more multidimensional approach, incorporating measures of social leisure activities (House et al. 1982) social support, social burden and/or perceived relationship quality (Fiori, Smith and Antonucci 2007; Fiori, Antonucci and Akiyama 2008; Cheng et al. 2009).

In the 1970's and 1980's, a number of epidemiological studies examined the impact of social network ties on mortality. Berkman and Syme (1979) conducted one of the first studies, and used data from the 1965 Human Population Laboratory Survey to study the influences of four sources of social contact (marital status, amount of contact with friends and relatives, church membership and informal/formal group membership) on mortality. These researchers also created a *Social Network Index* (SNI), where *intimate* contacts, defined by the variables marital status and contact with family and friends, were weighed more heavily than church or group affiliations. They found that respondents with each type of social contact had lower all-cause mortality rates than those lacking such a contact, and more intimate social contacts were stronger predictors of mortality than either church or group membership. Moreover, the age-adjusted relative risk for the most socially isolated compared to the most socially connected as measured by the SNI was 2.3 for men and 2.8 for women. Additional research using follow-up data from the Human Population Laboratory in Alameda County (Seeman et al. 1987), the Tecumseh Community Health Survey (House et al. 1982) and the Evans County Cardiovascular Epidemiologic Survey (Schoenbach et al. 1987) also used the same or similar variables in measuring social network ties and interaction.

More recent research has continued previous traditions, using similar variables to measure social networks. In an analysis of the effect of support structure on mental health, Lin, Ye and Ensel (1999) measured support *structure* through social club and organizational affiliations, number of weekly contacts, and whether the respondent had a spouse or partner. Some recent research included new variables to their estimation of social convoys, such as parental status, total number of (proximate) children, frequency of contact with children (Litwin 1997; Litwin 1998; Litwin 2001; Fiori et al. 2006), and the presence of a helpful neighbor (Litwin 1998). Lastly, in an effort to distinguish *supportive* or *helpful* social ties, researchers have incorporated measures of emotional support, instrumental support and emotional burden in their measures (Fiori et al. 2007; Fiori et al. 2008).

In an effort to quantify social networks, much previous research incorporated measures indicating the presence or absence of specific social relationships, such as marital or parental status, or measures of social functions, such as social support. Only few studies attempted to describe the characteristics of the respondents' actual social network structure or composition. In one of the first studies to measure the association of social network structure and health, Gallo (1982) measured network size, density, composition, proximity, duration, directedness and homogeneity among a sample of 60+ men and women living in Lowell, MA. Bowling and Browne (1991) used the Social Network Scale to obtain detailed information on total network size, composition, density, and number of close confidants and main helpers among a sample of respondents age 85+ living in two communities in the East End of London (although they supplemented this scale with items such as marital status, number of living children and frequency of contact). Among a small sample of adults, age 75+, who were born in Europe and living in Tel Aviv, Litwin (1999) used a network inventory to ask respondents to name persons who are important to them, generating information on network size, proportion of ties that are intimate, and network composition. Lastly, Fiori and colleagues (2007; 2008) used a network mapping technique developed by Antonucci (1986) to measure network structure, where individuals place their network members in one of three concentric circles, depending on closeness, and are asked questions regarding the relationships between each of the first ten alters listed.

2.4.2 Different Analytic Approaches

Throughout life, people are embedded in social networks that have an array of attributes. Many studies have used what will be referred to as a *variable-centered approach*, where they examine the separate contributions of each network attribute (or variable) to health. As noted above, a number of early studies examined the separate contributions to health of certain variables, including marital status, frequency of contact with friends, frequency of contact with family, church and group membership (Berkman & Syme 1979; House et al. 1982; Seeman et al. 1986; Schoenbach et al. 1987), network size, density, and homogeneity (Gallo 1982). Some researchers created an index, aggregating these above-mentioned variables into a composite or average measure to determine the "least" to "most" socially connected individuals (Berkman & Syme 1979; Seeman et al 1986; House et al. 1982).

Using what will be referred to as a *person-centered approach*, one vein of research has created social network typologies that represent the constellation of individuals' social network attributes. Thus, while researchers using a variable-centered approach may examine the influence of one or more variables, such as marital status, on health, those who use a person-centered approach attempt to combine multiple social network indicators into a meaningful typology that describes the features of individuals' networks. These social network typologies reflect the complex, multidimensional, and aggregate nature of social life (Fiori et al. 2006). This approach is compelling because social networks are more than the sum of their parts and contain emergent properties not explained by, or even represented in, their constituent parts (Blau 1977; Auslander and Litwin 1990; Smith and Christakis 2008). While social networks have their foundation in simple, dyadic interactions between pairs of actors, they also have their own attributes and dynamics apart from dyadic interaction (Blau 1977). Individuals interact with one another on a micro-level, but "produce extended structures that they had not imagined and in fact cannot see" (Kadushin 2011: 11). Thus, it is essential to try to capture the convergence of these social network attributes.

In one of the first efforts to detail individuals' personal social networks, Wenger (1997) found five different network types based primarily on measures of availability and contact with family, friends, neighbors and involvement in the community. She used data from an intensive, 4-year long qualitative study of 25 community-dwelling elderly persons aged 79+ living in Wales. Although Wenger's sample was small, she observed five network types: (1) locally integrated, (2) wider-community focused, (3) local self-contained, (4) local family dependent, and (5) private restricted. Locally integrated support networks were the most common, characterized by informal help to and from local family, friends and neighbors and high community involvement. Wider-community focused networks were similar to locally integrated networks except for an absence of local kin (although there was contact with more distant kin). Local self-contained networks were characterized by help to and from neighbors and low community involvement. Local family dependent networks consisted of reliance on local family and some neighbors, with low levels of community involvement. Finally, private restricted networks exhibited an absence of local kin, no local source of informal support and little community involvement.

Studies of community-dwelling older adults in the U.S. (Fiori et al. 2006; Fiori et al. 2008), Germany (Fiori 2007), Israel (Litwin 1997; Litwin 1998; Litwin and Landau

2000; Litwin 2001; Litwin and Shiovitz-Ezra 2006), Japan (Fiori et al. 2008) and China (Cheng et al. 2009), using larger samples and quantitative methods, report social network types somewhat similar to those of Wenger. While these studies use different criterion variables in assessing social convoy typologies, they have consistently found four main social network types: diverse, family-focused, friend-focused and restricted. Typically, compared to restricted networks, more diverse network types have been associated with increased and more recent healthcare utilization (Litwin 1997), higher morale (Litwin 2001), higher levels of well-being, life satisfaction (Fiori et al. 2007; Cheng et al. 2009), increased probability of survival (Litwin and Shiovitz-Ezra 2006; Fiori et al. 2008), lower morbidity (Litwin 1998; Fiori et al. 2007), and fewer depressive symptoms (Fiori et al. 2006; Fiori et al. 2007; Cheng et al. 2009). In only one study, using a community-based sample of older adults in Yokohama, Japan, did researchers not find a relationship between social network type and measures of mental or physical health (Fiori et al. 2008).

2.4.3 Different Moderators

Some early epidemiological studies examined whether demographic factors, such as gender, age or race, altered the overall effect of social network ties on mortality. Researchers examined these potential moderators by assessing the influence of network ties on age-, gender-, or race-specific mortality rates. House, Robbins and Metzner (1986) found that the positive relationship between social connectedness and longevity was statistically significant only for men in their sample, while Schoenbach and colleagues (1986) found social connectedness to be predictive of mortality for white men only (it was only a weak and not statistically significant predictor for white women, black men and black women). Seeman and colleagues (1987) found age to be an important factor in understanding which types of social relationships were most important. For those in their sample less than 60 years of age, marital status assumed a primary role, but social ties with close friends and relatives assumed greater importance to those over 60 years of age (Seeman et. al, 1987). More recently, a study found membership in diverse and friend-focused social network types to be protective against mortality when compared with membership in a restricted network, although this was true for only those who were 70 years of age or older (Litwin and Shiovitz-Ezra 2006). Lastly, Peek and Lin (1999) report that age is a moderator in the effect of kin composition on mental health among a sample of older adults. Thus, past research has identified the need to examine demographic factors such as age, gender and race as potential moderators of the network-health relationship.

2.5 Social Causation vs. Social Selection

While many studies have documented the association of larger and more diverse social networks with better physical and mental health outcomes, longitudinal data are needed to ascertain whether this is the result of social causation or social selection. The social causation explanation posits that social networks directly or indirectly influence mental and physical health. Scholars have proposed that social networks may indirectly influence well-being through a number of potential pathways, including through the provision of emotional support (e.g., the sense that one is loved and cared for), instrumental support (e.g., help with tasks), and informational (e.g., advice) social support, access to material resources, social influence, social control, social engagement and attachment (Umberson, Crosnoe and Reczek 2010; Berkman and Glass 2000).

Alternatively, the social selection explanation posits that individuals with better mental or physical health select into larger, more diverse social networks while those with worse health select into smaller, more restrictive networks. It may be difficult for individuals who suffer from physical health problems or poor mental health to initiate social contact or attract social relationships. They may face a higher likelihood of social rejection when attempts at initiating social relationships are made. Lastly, it may be difficult for unhealthy individuals to maintain their existing social relationships due to social withdrawal or avoidance by loved ones and peers (Coyne 1976). While many of the previously mentioned studies that examined the influence of social networks ties and connectedness on mortality provide some support for social causation, most literature on social networks and health remains cross-sectional.

Recently, scholars have pointed out that what has been the dominant perspective in the health literature, namely the unidirectional view of networks influencing health, may be misleading. The connections between networks and health are likely due to reciprocal, dynamic processes. Thus, it is important to consider the effects of health on networks to avoid biasing the estimates of the effect of social networks on health. By failing to take into account endogenous health effects, researchers may overestimate the influence of networks on health (Haas et al. 2010).

Health is an integral component of continued participation in social interaction and activities. Health also affects individuals' position within a network. Older adults with better health status receive more "time-spent" nominations from their peers even after controlling for the number of nominations they sent out, indicating that perhaps healthier seniors enjoy higher social status compared to their less healthy counterparts (Schafer 2011). Moreover, healthy seniors have positional advantages within their social network, with fewer network constraints, more network integration (Schafer 2012) and a higher likelihood of bridging structural holes (Cornwell 2009a; Cornwell 2009b). Health enables people to occupy positions of power and independence within a network (Cornwell 2009a).

The above-mentioned studies posit a social selection mechanism, but use cross-sectional network data. Longitudinal data from Add Health has provided additional evidence in support of social selection processes. Depressed adolescents have lower levels of social integration due to withdrawal from social network ties over time (Schaefer, Korniekno and Fox 2011), and adolescents with poor self-rated health receive fewer nominations from peers over time, are more likely to become social isolates, and occupy less central/ more marginal positions in the network over time compared to their healthier counterparts (Haas et al. 2010).

In an attempt to distinguish between processes of social causation and social selection, this dissertation will measure the predictive value of social convoys on changes in self-rated health, psychological distress and self-esteem across time, from 1986 to 1986, and from 1989 to 1994. In addition, the final analytic chapter will examine the dynamic, reciprocal relationships between social networks and self-rated health, psychological distress and self-esteem through the use of autoregressive cross-lagged models within a structural equation framework.

2.6 Social Location and Social Convoys

The structural and compositional aspects of a social network determine, in part, the giving and receiving of social support, as well as other social resources. Variations in social network characteristics, and consequently social resources, are due to the social locations of actors, which influences the formation of social ties (Pugliesi and Shook 1998). The formation of social ties depends on social contact, with structural factors precluding or making possible social contact between actors (Blau 1977). Social network characteristics are patterned by gender (Antonucci and Akiyama 1987; Adams and Blieszner 1995; Pugliesi and Shook 1998), age (Marsden 1988; Ajrouch, Antonucci and Janevic 2001), race and ethnicity (Ajrouch et al. 2001; Peek and O'Neill 2001; Barnes et al. 2004), marital status (Hurlbert and Acock 1990), and socioeconomic status (Campbell, Marsden and Hurlbert 1986; Marsden 1988). These demographic factors also are strongly related to mental and physical health, and may be potential confounding variables in the forthcoming analyses. Thus, it is important to take them into account as control variables in the forthcoming analyses examining the effect of social networks on health.

2.6 Conclusion

This study builds on existing literature in important ways. First, this study uses data on respondent reports of close confidants to measure the structure and composition of social networks, bridging developments in social network analysis with the social convoy model used in the health literature. Second, this study compares the predictive utility of a variable-centered vs. person-centered approach to modeling social networks. In using a person-centered approach, I create social network typologies, which reflect the complex and multidimensional nature of social networks in real life. These typologies are strongly correlated with important social and demographic factors, such as age, gender, race, and socioeconomic status. Third, I examine the association of the social convoy typologies with various indicators of health, including self-rated health, psychological distress and self-esteem, as well as examine age, gender and race as potential moderators of this association. Next, I examine whether the social network typologies I developed predict changes in self-rated health, psychological distress and self-esteem over the course of 3 and 8 years. Lastly, I address the dynamic, reciprocal relationship between health and networks through studying how changes in social networks affect health, and how changes in health affect social networks.

3. Study Design

The Americans' Changing Lives (ACL) study is a longitudinal, panel survey conducted by the Survey Research Center at the University of Michigan. The ACL was designed to understand the role of a broad range of psychological, social and behavioral factors in enabling and maintaining the health and functioning of individuals as they age (House, Lantz and Herd 2005). The ACL is the best data source for this dissertation research for a number of reasons. First, the ACL is a nationally-representative, longitudinal panel survey, collecting information on respondents across multiple waves of data. Second, the ACL contains information on personal networks of respondent-reported close confidants. The first wave of the survey has the most comprehensive picture of personal networks, including information on total network size, density and the gender and relationship of the first three reported close confidants; the later three waves of data collect more limited profiles of information. Third, as stated above, this data source also contains a wealth of information on various indicators of mental health, physical health, functioning and mortality. Thus, this data set is well-suited for the examination of the relationships between social networks and mental and physical health, both in cross-sectional analyses and over time.

In this chapter, I describe the Americans' Changing Lives study in depth, including the study design and patterns of attrition due to non-participation and mortality. I then introduce the measures I use throughout the rest of the dissertation, including primary independent, dependent and control variables. Lastly, I discuss the analytical methods used in the dissertation, including hierarchical cluster analysis, various regression models (ordinary least squares, Poisson and logistic regression), structural equation modeling and autoregressive cross-lagged models.

3.1 Data Source

The ACL is a nationally representative panel study of 3,617 U.S. adults, with interviews conducted in 1986, 1989, 1994, 2001/2002 and 2011. This dataset covers a wide range of topics of interest to sociologists, psychologists and health researchers, and includes questions on demographic factors, socioeconomic status, interpersonal relationships, social interaction and support, life events, health behaviors, health care utilization, and mental and physical health measures. The sample consists of persons who were 25 years of age or older and living in the continental United States at the time of the baseline survey.

Multiple studies have used the ACL to examine the health effects of marital status (Umberson 1992a; Lui and Umberson 2008), romantic relationships (Moorman, Booth and Fingerman 2006), parental status (Umberson 1992b), social involvement (Tang 2009), social support (Schnittaker 2007) and social convoys (Fiori et al. 2006). Additional studies have also used this data source to examine how the loss of a potentially important network member through life transitions such as divorce, widowhood (Williams and Umberson 2004) and parental bereavement (Umberson 2003) influence health. In a similar vein to this dissertation, Fiori, Antonucci and Cortina (2006) used the ACL to construct a social convoy typology and explore the cross-sectional associations of social convoy types with depression. Although the authors made use of the same data source, they did not use information on respondent reports of close confidants to measure social convoys, but instead relied on other variables measuring marital status, total number of children, frequency of contact with children, frequency of contact with friends, church attendance and informal organization attendance. This dissertation uses the information on respondent reports of close confidants to further our understanding of the influence personal networks (or social convoys) on an array of mental and physical health indicators.

3.1.1 Study Design

The ACL sample is a nationally representative cross-section of non-institutionalized persons 25 years of age or older and living in the continental United States in 1986. The identification of the sample respondents was conducted using a four stage sampling process: (1) primary stage sampling of U.S. Standard Metropolitan Statistical Areas (SMSA's) and counties; (2) second stage sampling of area segments; (3) third stage sampling of housing units within the sampled area segments; and (4) random selection of a respondent from the selected households (House 2003). In addition, if a woman's husband was 65+ years of age and selected for an interview, the married woman was also included into the sample with certainty (House 2003). The ACL disproportionately sampled Blacks (2:1) and those 60 years of age or older (2:1). Thus, the compounding of oversampling for race and age means that Black older adults (60+ years of age) are disproportionately sampled 4:1.

The first wave of data collection occurred in 1986, and had an individual response rate of 68% (N=3,617) and a household response rate of 70% (House, Lantz and Herd 2005). The second wave of data was collected in 1989 and researchers attempted to contact all respondents who participated in the first wave. Wave 2 was an 89-minute face-to-face re-interview of survivors (N=2,867), with a survivor response rate of 83%. The third wave of data was collected in 1994, and again, an attempt was made to contact all respondents from the first and second waves. Wave 3 was a 45-minute telephone or face-to-face re-interview (N=2,562), with a survivor response rate of 83%, including 164 proxy interviews. Although five waves of data are available, only the first four waves are publicly available through the Inter-University Consortium for Political and Social Research (ICPSR). The longitudinal analyses presented here make use of only the first three waves for the following reasons. First, the sample size between the third and fourth wave drops dramatically from N = 2,562 to N= 1,787; the sample size drops further to N=1427 in the fifth wave of data. Second, the time between the third and fourth waves of data is 8 years, and between the fourth and fifth waves of data collection is 10 years, both of which are much longer than the time between any of the previous waves of data.

3.1.2 Sample Attrition

Sample attrition over the first three waves of survey data is significant. Of the 3,617 respondents from the first wave of the study, 79% also participated in the second wave. Of the 21% who did not participate in the second wave, 16% (N = 584) were lost due to non-participation and 5% (N = 166) had died. Only 71% of the baseline respondents participated in the third wave of data. Of the 29% who did not participate in the third wave, 14% (N = 509) were lost due to non-participation and 15% (N = 546) had died. Sixty-four percent of the 3,617 baseline respondents participated in all three waves of data, 14% participated in only the first two waves of data, 6% participated in the first and third waves of data and 15% only participated in the first wave of data collection.

I analyzed sample attrition during the eight year period, from 1986 to 1994. I used multinomial logistic regression to predict loss to follow-up from non-participation and death by the independent, dependent and control variables of interest in this dissertation. For ease of interpretation, Table 1 presents the odds ratios that were calculated through exponentiation of the models' parameter estimates.

Table 1: Odds Ratios from the Multinomial Regression of Sample Attrition on Baseline Variables of Interest, ACL 1986-1994.

	Wave 2		**Wave 3**	
	Non-Response	Death	Non-Response	Death
Network Structure:				
Size (Instrumental)	0.984	0.986	0.954**	1.005
Size (Emotional)	0.979	0.975	1.005	0.953
Density	1.018	1.045	1.022	0.978
Network Composition:				
Partner Nomination	1.131	0.736	1.043	0.824
Family Nomination	1.120	1.100	0.960	1.003
Friend Nomination	0.932	0.759	1.078	0.878
Gender Homophily	0.752†	1.027	0.710*	1.194
Demographic Factors:				
Age	0.995	1.060***	0.986***	1.077***
Female	0.819†	0.375***	1.050	0.314***
Black	1.327**	1.316	1.554***	1.351*
Married	0.872	0.864	0.762*	0.868
Total # Children	0.910***	0.969	0.936*	0.951*
Education (Years)	0.947**	0.996	0.951**	0.985
Income (logged $)	0.952	0.721**	0.891†	0.753***
Health Indicators:				
Self-Rated Health	0.982	0.708***	0.953	0.740***
Psychological Distress	1.189	1.146	1.006	1.368†
Self-Esteem	0.940	0.980	0.984	1.032
Likelihood Ratio	4142.53	4142.53	4887.57	4887.57

*** p < 0.001 ** p < 0.01 * p < 0.05 † p < 0.10

Notes: The reference category for the dependent variables is participation in that wave of data collection.

Baseline respondents who declined to participate in the second wave of data collection were more likely to have identified as Black (OR = 1.327), and had fewer children (OR = 0.910) and fewer years of education (OR = 0.947) than Wave 2 participants. Baseline respondents who were older (1.06) and who reported lower levels of self-rated health (OR = 0.708) had an increased odds of having died before the second wave of data collection compared to their younger, healthier counterparts. Women (OR = 0.375) and individuals with higher levels of income (OR = 0.721) had a decreased odds of dying before Wave 2 compared to men and those with lower incomes. Similar to results found for Wave 2, Black race (OR = 1.554), total number of children (OR = 0.936) and education (OR = 0.951) predicted non-response in the third wave of data collection. In addition, individuals who were older (OR = 0.986), married (OR = 0.762), who reported larger instrumentally helpful social ties (OR = 0.954) and a larger proportion of gender homophilous ties (OR = 0.71) had a lower odds of non-response in the third wave of data collection. Lastly, similar to results observed for Wave 2, age (OR = 1.077), female gender (OR = 0.314), income (OR = 0.753) and self-rated health (OR = 0.74) were predictive of mortality by the third wave of data collection. In addition, Black respondents (OR = 1.351) had an increased odds of dying by Wave 3 compared to their white counterparts, while respondents with more children (OR = 0.951) had a decreased odds of dying before the Wave 3.

3.1.3 Correction for Sampling Design and Non-Response

The Americans' Changing Lives survey uses a complex, disproportionate sampling design, oversampling older adults and Blacks, and violating assumptions of independent observations by including in the sample the wives of older, male respondents. Indeed, most major population surveys do not use simple random sampling, but have complex sampling designs, where the sampling units (e.g., individuals) have different probabilities of being selected into the sample. Often times, the reason behind complex sampling schemes, such as oversampling of particular groups, is to minimize the standard errors associated with these parameters of interest (Winship and Radbill 1994). Sampling weights are then developed to make the distribution of a set of variables in the data approximate to the distribution of those variables in the population from which the sample was drawn (Winship and Radbill 1994).

It is widely accepted among research analysts that sampling weights, often called population weights, be used to obtain unbiased estimates of descriptive, univariate population characteristics (Pfefferman 1993; Winship and Radbill 1994). Controversy remains, however, over the role of sampling weights for analytical inference, when assessing the influence of a series of independent variables on a dependent variable of interest. While some analysts largely ignore sampling weights in their causal models, others often include sampling weights in every analysis (Pfefferman 1993).

Winship and Radbill (1994) set forth a number of guidelines to use when considering incorporating sampling weights into OLS regression models. The authors suggest comparing unweighted and weighted analytical models to see if the results differ. In cases where the sampling weights are solely a function of the independent variables and the weighted and unweighted parameter estimates are substantively *similar*, then unweighted estimates are preferable. Although both yield unbiased and consistent estimates, the unweighted estimates are more efficient than the weighted estimates, with smaller standard errors. On the other hand, if the weighted and unweighted parameter estimates are significantly *different*, this could be due to two reasons. First, the model may not be correctly specified, lacking important linear, non-linear and/or interaction terms, and resulting in omitted variable bias. Having parameter estimates that differ by whether or not weights are applied in the model may be a hint that the model is not correctly specified. Second, weighted and unweighted parameter estimates may significantly differ when the weights are a function of the dependent variable of interest. When sampling weights are a function of the dependent variable, the use of sampling weights in analysis may be appropriate. In this case, the weights may correct for sample selection bias, but the weighted model may still yield incorrect standard errors. The authors advocate adjusting the standard errors using the White heteroskedastic consistent estimator.

The composite weighting variable recommended for use in descriptive analyses of the first wave of the ACL is a formed as the product of five components parts: (1) housing unit selection weight; (2) household screening factor; (3) respondent selection factor; (4) nonresponse adjustment weight; and (5) post-stratification weight. The weights generated for the second and third wave of the ACL are computed beginning with the nonresponse adjusted weights from the first wave. These weights are then adjusted for nonresponse, after which post-stratification weights are applied.

In accordance with the guidelines proposed by Winship and Radbill (1994), each analytic model presented in this dissertation is tested using both weighted and unweighted data. Where the parameter estimates are substantively similar, I present results from the unweighted analyses because, as stated above, unweighted parameter estimates are more efficient due to smaller standard errors. In cases where the sampling weights are a function of the dependent variable, and the model cannot be respecified, weighted parameter estimates are presented.

3.1.4 Analytic Sample

The first empirical chapter uses data from the first wave of the ACL to construct social convoy typologies and examine their univariate relationships with important social, demographic and health factors. The analytical sample for the first chapter consists of those respondents who participated in Wave 1, but did not have missing information on any health-related variables of interest, which will serve as dependent variables in the second empirical chapter. Psychological distress is a composite measure composed of 11 indicators, while self-esteem is a composite measure composed of 3 indicators. Twenty respondents who had missing information on *more* than 3 indicators of psychological distress were coded as missing (".") for psychological distress. Similarly, twenty-six respondents who had missing information on *more* than one indicator of self-esteem were coded as missing (".") for self-esteem. Thus, while 3,617 respondents participated in Wave 1, a total of 40 respondents had missing information on one or both composite measures of psychological distress or self-esteem. No respondent had missing information on self-rated health. Thus, the final analytical sample for the first empirical chapter (and all other cross-sectional analyses) is N = 3,577.

The second empirical chapter examines the cross-sectional association between social network typologies and three health indicators (self-rated health, psychological distress and self-esteem). The analytic sample for this cross-sectional analysis is the same as for the first empirical paper (N = 3,577). In addition, the second empirical chapter examines how social network types predict changes in health over time, from Wave 1 (1986) to Wave 2 (1989) and from Wave 1 to Wave 3 (1994). In order to make the best use of the data available, the longitudinal analyses presented in Chapter 2 will use two separate samples.

The first longitudinal analysis will use social network typologies to predict changes in health from Wave 1 (1986) to Wave 2 (1989). The sample used for this analysis is composed of only those baseline respondents who participated in the second wave of data collection and had no missing data for self-rated health, psychological distress or self-esteem in either the first and/or second waves of data. Again, respondents who had missing information on *more* than 3 indicators of psychological distress were coded as missing (".") for psychological distress and respondents who had missing information on *more* than one indicator of self-esteem were coded as missing (".") for self-esteem in Wave 2. Of the 3,577 respondents used in the cross-sectional analyses, 2,839 participated in Wave 2. Of these, twenty-seven respondents were coded as having missing information on psychological distress or/and self-esteem, leaving a final sample of N = 2,812.

The next longitudinal analysis will use social network typologies to predict changes in health from Wave 1 (1986) to Wave 3 (1994). Of the 3,577 respondents used in the cross-sectional analyses, 2,540 participated in the third wave of data collection. Of these, 180 respondents were coded as having missing information on psychological distress or/and self-esteem, leaving a final sample of N = 2,360. The two samples used in these longitudinal analyses are not comparable with each other because they contain different respondents due to sample attrition over time. In addition, while 14% of the baseline sample participated in only the first and second waves of data, 6% of the baseline sample participated in only the first and third waves of data collection.

The last empirical chapter uses structural equation modeling to examine the dynamic, reciprocal nature of networks and health, namely, how changes in social networks affect health, and how changes in health affect social networks. In this chapter, I make full use of all available information using full-information maximum likelihood (FIML) using MPLUS.

3.2 Measures

3.2.1 Independent Variables

The primary independent variables of interest measure network structure and network composition. The network structure variables include size of network providing emotional support, size of network providing instrumental support and network density. The size of network providing emotional support refers to the number of persons the respondent reported as close confidants and was measured by the question, "Is there anyone in your life with whom you can really share your very private feelings and concerns? How many such persons are there?" The size of network providing instrumental support was derived from a question asking, "About how many friends or other relatives do you have whom you could call on for advice or help if you needed it?" The size of the network providing instrumental support is highly skewed, ranging from 0 to 95, with 75% of the sample reporting 10 or fewer instrumentally supportive network members. Therefore, this variable has been truncated with a cut-off value of 11, where respondents reporting greater than 10 instrumentally supportive network members are assigned the cutoff value. Network density is the extent to which members of one's social network know and interact with each other. This was measured from a question asking, "Finally, thinking of ALL the family or friends you feel close to, whom you could call on for advice or help if you needed it, how many of these people are close to each other in the same way?" Response categories were reverse-coded and include "none" (1), "less than half" (2), "about half" (3), "most" (4), and "all" (5).

The network composition variables represent the gender and relationship type of each reported closest confidant. For up to three close confidants, respondents were asked the confidants' gender (male/female) and their relationship to each. Gender composition of the network was measured in two ways. First, in descriptive analyses I report gender homophily or the percentage of close confidants that are of the same gender as the respondent. For the construction of social network types, I measure gender composition through three dichotomous variables, indicating whether respondents' networks of close confidants were all women (1 = yes, 0 = no), all men (1 = yes, 0 = no) or of mixed gender composed of both women and men (1 = yes, 0 = no). Relationship types are measured using three binary variables indicating whether the respondent nominated as a close confidant: 1) their partner, ex-partner or spouse, (2) at least one family member or (3) at least one friend. An overwhelming majority of non-kin confidants were identified as "friends" of the respondents and thus this category is labeled accordingly. A much smaller proportion of non-kin confidants were identified as neighbors, clergy members or priests, and co-workers, business partners or bosses. These nominations were also included as "friend" nominations. The reference category is made up of respondents who reported having no close confidants, and therefore have no information on gender or relationship type.

3.2.2 Control Variables.

Several background factors are associated with social networks and mental and physical health. These variables may confound the relationship between social networks and health, and thus are controlled in all analyses. These variables include age, gender, race, marital status, total number of children, education, and income. Age is a continuous variable. Gender (0 = male, 1 = female), race (1 = Black, 0 = other) and marital status (1= married, 0 = other) were measured as binary variables. Total number of children is a count variable, which takes into account the total number of children living within the household and elsewhere. Education is measured by two binary variables indicating whether the respondent obtained a high school diploma/GED (1= yes, 0 = no) and whether the respondent obtained a bachelor's degree or higher (1 = yes, 0= no). The reference category is less than a high school diploma/GED. Income is total family income within the last 12 months. Respondents were assigned the mid-point dollar value of their reported income category and this value was then logged.

3.2.3 Dependent Variables

Self-rated health was measured by asking respondents, "How would you rate your health at the present time?" Original response categories included: "excellent," "very good," "good," "fair" and "poor." The five-category self-rated health variable was highly skewed, with slightly over 78% of respondents reporting "good" to "excellent" health.

Therefore, for cross-sectional analyses, a binary measure of poor/fair self-rated health was constructed (1=fair/poor and 0 = good/very good/excellent).

Psychological distress was measured using the 11-item short form of the CESD. These eleven items asked the respondents how often in the past week they felt: “depressed,” “everything I did was an effort,” “my sleep was restless,” “happy,” “lonely,” “people were unfriendly,” “I enjoyed life,” “I did not feel like eating,” “my appetite was poor,” “sad,” “that people disliked me,” and “I could not get “going.” Original response categories include: “hardly ever,” “some of the time” and “most of the time.” Initially, positive items were reverse-coded, so higher scores on the scale represented higher levels of psychological distress. I formed a composite measure of psychological distress, ranging from 11 to 33. This continuous measure was highly skewed to the right, despite numerous efforts at transformation. Thus, the cross-sectional analyses presented here use negative binomial regression to model the count of depressive symptoms. Respondents who indicated that they experienced a symptom “some of the time” or “most of the time” were coded as having that symptom. The total count of depressive symptoms ranged from 0 to 11.

Self-esteem is measured using three items. Respondents were asked the extent to which they agreed with the following three statements, “I take a positive attitude toward myself”, “at times I think I am no good at all” and “all in all, I am inclined to feel that I am a failure”. Response categories ranged from “strongly agree” (1) to “strongly disagree” (4). Initially, positive items were reverse-coded, so higher scores on the scale represented higher levels of self-esteem. This composite measure of self-esteem ranged from 3 to 12, but was highly skewed to the left, despite various efforts at transformation.

Therefore, in cross-sectional analyses, self-esteem is measured as a binary indicator of high self-esteem. Respondents with a score of 9 or higher were coded as having high self-esteem. This is because approximately 82% of the sample scored 9 or higher on self-esteem, which displayed a mean of 10.2, median of 11 and mode of 12.

3.3 Descriptive Statistics

Table 2 presents the descriptive statistics for the baseline ACL sample. As discussed previously, this sample consists of all ACL respondents who participated in the first wave of data collection and were not coded as having missing information on any dependent variables of interest in that wave. The average age of the sample is 54 years, with ages ranging from 24 to 96 years. Approximately 63% of the respondents are women, 33% identify as being black or African-American and 55% are married. The average respondent reports having over 2 children, slightly less than 12 years of schooling and an average income of $23.5k; there is a large amount of variability in total number of children, education and income across the sample. The sample reports an average of 6 instrumentally helpful network members and 2 emotionally-close confidants, with a little more than half of these network members close to each other in the same way. Fourteen percent of the sample reported not having a close confidant. Among the 86% of the sample who reported at least one close confidant, a third nominated a spouse, fiancé, partner or ex-partner as a close confidant, while over half nominated a family member and/or a friend. Among those who reported having one or more close confidants, a little more than half of the social ties were same-gender ties. The second column in Table 2 provides descriptive statistics for the weighted sample.

Applying weights ensures that the sample is representative of the population from which it was drawn. As portrayed in the Table 2, the weighted ACL sample is different from the unweighted sample primarily in terms of demographic factors, including age, gender, race, marital status and socioeconomic status. The weighted sample is younger, more likely to be male, white, married, and report more years of education and a higher total annual income. The weighted and unweighted samples are relatively similar in regards to health indicators of interest and network structure and composition, with the exception that the weighted sample is more likely to nominate a partner/spouse as a confidant (an artifact of the sample also being more likely to be married).

Table 2: Descriptive Statistics in Means (Percentages) for the American Changing Lives Baseline Sample, 1986 (N = 3,577).

	Unweighted		**Weighted**	
	Means (%)	Std. (N)	Means (%)	Std. (N)
Network Structure:				
Size (Instrumental)	6.28	3.59	6.75	3.54
Size (Emotional)	2.21	1.78	2.32	1.79
Density [1]	3.33	1.35	3.21	1.31
Network Composition:				
Reported No Close Confidants	(14.17)	(507)	(11.82)	(424.29)
Reported 1+ Close Confidants:	(85.83)	(3070)	(88.18)	(3164.50)
Nominated Partner	(35.02)	(1075)	(48.58)	(1537.37)
Nominated Family Member	(55.9)	(1716)	(51.47)	(1628.87)
Nominated Friend/ Non-Kin	(51.47)	(1580)	(51.5)	(1629.64)
Gender Homophily	58.87	38.41	54.39	38.67
Demographic:				
Age	53.55	17.61	47.05	16.43
Female	(62.45)	(2234)	(52.88)	(1897.89)
Black	(32.35)	(1157)	(10.95)	(392.93)
Married	(54.79)	(1960)	(69.49)	(2493.83)
Total # Children	2.61	2.07	2.36	1.84
Education (Years)	11.50	3.45	12.37	3.13
Income	$23,442.13	$21,999.86	$30,522.49	$24,103.47
Health Indicators:				
Self-Rated Health [2]	2.51	1.13	2.30	1.07
Psychological Distress [3]	1.43	0.37	1.40	0.35
Self-Esteem [4]	3.40	0.61	3.41	0.59

Notes: [1] Network density was measured on a scale of 1 to 5, where higher values indicate higher density. [2] Self-rated health is measured on a scale of 1 to 5, where higher values indicate better health. [3] Psychological distresses is a composite measure composed of 11 indicators, with a scale of 1 to 3. Higher values indicate higher levels of distress. [4] Self-esteem is a composite measure composed of 3 indicators, with a scale of 1 to 4. Higher values indicate higher levels of self-esteem.

3.4 Analytic Methods

3.4.1 Methods for Cluster Analysis

Standard clustering methods include hierarchical cluster analysis and *k*-means clustering. Hierarchical cluster analysis was chosen for this dissertation because of its superior ability to detect clusters and flexibility with regard to data form. Within agglomerative methods of hierarchical cluster analysis, each observation begins as a cluster by itself. The two closest clusters are then merged together to form a new cluster, with the merging of the two closest clusters repeated until only one cluster is left. This method offers flexibility in regards to the type of variables used, allowing for data in the form of coordinates or distances (SAS 2013).

The disadvantage of hierarchical methods is that once fusions in the data are made, they are irrevocable. Thus, when two individuals or clusters have been joined together they cannot be separated. Since agglomerative hierarchical methods ultimately reduce the data to a single cluster containing all individuals, deciding on the correct number of clusters for an optimal solution is tricky (Everitt, et al. 2011). Hierarchical cluster analysis produces a history of the clustering process (through dendograms or tree diagrams), as well as useful statistics for estimating the number of clusters in the population from which the data are sampled.

The *k*-means method of clustering consists of defining an initial partition of individuals into clusters, calculating the change in the clustering criterion produced by moving each individual into a different cluster, making the change which leads to the greatest improvement in the clustering criterion, and iteratively repeating this process until no movement of individuals into different clusters will further improve the clustering criterion (Everitt, et al. 2011). While selection of an initial partition in the data can be performed a number of ways, the results may be radically different depending on the initial partition used (Everitt, et al. 2011). *K*-means uses only continuous variables, thus allowing only for data in the form of distances, and is designed to find good clusters (not best clusters) through 3 to 4 passes through the data (SAS 2013). While *k*-means clustering is a good method to use for large datasets because of its superior efficiency, hierarchical cluster analysis has a superior ability to detect clusters in the data.

Hierarchical cluster analysis can use different procedures to determine how the distance between two clusters is calculated (SAS 2013). In this hierarchical cluster analysis, I use Ward's minimum-variance method. The network structure indicators are continuous variables and the network composition indicators are binary variables. Initial cluster analysis combining the network structure and composition indicators resulted in cluster solutions dominated by the binary variables. This is a similar issue to that reported by Cheng and colleagues (2009), who chose not to use a binary indicator of marriage in their cluster analysis because of the resulting exaggerated differences between those with and without a spouse. They also cite previous work on social convoy typologies where inclusion of a binary indicator of marriage dominated the analysis, and was ultimately the deciding factor on cluster differentiation, with resulting clusters composed solely of the married or unmarried (Cheng et al. 2009). To resolved this potential issue, cluster analyses were performed separately for the network structure (continuous) and network composition (binary) indicators.

Before conducting the cluster analyses on the network structure indicators, the network structure variables were standardized as z-scores to eliminate the effects caused by differences in scale. The transformation of continuous variables using z-scores has been shown to be highly effective in cluster recovery using Ward's minimum-variance method (Milligan and Cooper 1988). Euclidean distances between points were used as the dissimilarity measure (Everitt et al. 2001). Inspection of the dendogram, and pseudo F (PSF) and t^2 (PST2) statistics pointed to a 4- or 6- cluster solution for social network structure. After inspecting 4-, 5- and 6- cluster solutions, I determined that the 4-cluster solution was optimal given the frequency of the criterion variables and the desire to preserve important distinctions in the data.

The social composition variables are binary, and therefore, I created a Jaccard distance matrix as input for the hierarchical clustering procedure (Everitt et al. 2001). Inspection of the pseudo F (PSF), *t2* (PST2) statistic and dendrogram pointed to either a 3, 4- or 7- cluster solution. Repeating the above procedure, I inspected the 3-, 4-, 5-, 6- and 7- cluster solutions, determining the 7-cluster solution was optimal given the frequency of the criterion variables and the desire to preserve important distinctions in the data.

3.4.2. Methods for Cross-sectional Analyses

Negative binomial regression was used to assess the cross-sectional association between counts of depressive symptoms and social network types. In modeling count data, negative binomial regression has greater flexibility and more relaxed assumptions than the Poisson model (Gardner, Mulvey and Shaw 1995). As is true with most count data, the sample variance ($\sigma^2 = 16.4$) of count of depressive symptoms is larger than the sample mean ($\bar{x} = 15.8$), thus violating an assumption of the Poisson model. Negative binomial models are similar to Poisson models in that they predict count outcomes, but negative binomial models include a parameter, σ^2, that accounts for this over-dispersion (McCullagh and Nelder 1989).

As stated previously, due to a high degree of skew for the variable representing self-rated health and the composite measure representing self-esteem, these health outcomes were dichotomized. I use logistic regression to model the associations between reports of poor/fair self-rated health and social network types, and high self-esteem and social network types.

In all analyses, a series of hierarchically nested models is presented. Model 1 regresses the dependent variable on demographic and background variables. Model 2 adds the social network structure types and Model 3 adds the social network composition types to Model 1. Model 4 includes demographic variables, network structure and network composition types. Findings with and without applying sample weights were similar and so results presented below are unweighted. All cross-sectional analyses were run with SAS 9.13, using multiple imputation to correct for missing data.

3.4.3 Methods for Longitudinal Analyses: Residual Change Scores

The first set of longitudinal analyses uses the social network typologies to predict self-rated health, psychological distress and self-esteem at Wave 2 (1989) and Wave 3 (1994), after controlling for baseline health status (measured in 1986). This method has been called the regressor variable method (Allison 1994) or residualized change score method, and has been used to examine change in dependent variables between waves. The aim of this method is to examine the relationship between an independent variable, X, and a dependent variable, $Y_{2,}$ while controlling for the effects of Y_1. Here, Y_1 and Y_2 are measurements of the same variable at two different points in time. This method of studying change essentially treats the Y_1 variable as a control variable (Allison 1990). Using residualized change scores takes into account the baseline differences between respondents in health status.

Another way of measuring change between two points in time has been the change score method, where the difference between Y_2 and Y_1 is regressed on the independent variable, X. Previously, researchers objected to the use of this method for two main reasons: (1) change scores are less reliable than their component variables; and (2) they are biased by regression towards the mean, meaning that individuals with high scores at time 1 (Y_1) will tend to score lower at time 2 (Y_2), while individuals with low scores at time 1 (Y_1) will tend to score higher at time 2 (Y_1) (Allison 1990). The residualized change score method has been referred to as the *conventional* way of measuring change over time in the social sciences, although Paul Allison has advocated using change scores as a superior method of studying change under certain circumstances (1990).

This dissertation will present two sets of results using the residualized change score method. The first analysis will use ordinary least squares (OLS) regression to regress the continuous indicators of health (self-rated health, psychological distress and self-esteem) at *Wave 2* on the social network typologies, while controlling for baseline health status. Similarly, the second analysis will use ordinary least squares (OLS) regression to regress the continuous indicators of health (self-rated health, psychological distress and self-esteem) at *Wave 3* on the social network typologies, while controlling for baseline health status. Results obtained from using OLS regression to model change scores are also provided for comparison (see Appendices M – O).

3.4.4 Methods for Longitudinal Analyses: Autoregressive Cross-lagged Models in SEM

The third empirical chapter in this dissertation tests hypothesis derived from social causation and social selection explanations for the network – health connection. With data from the first (1986) and second (1989) waves of the ACL, I will use autoregressive cross-lagged models within a structural equation framework to simultaneously assess the influences of social networks on health status and health status on social networks.

Structural equation modeling (SEM), also known as covariance structural analysis, is a useful approach to data analysis for a number of reasons. First, structural equation models can simultaneously estimate regression equations where variables are treated as both *predictors* (independent variables) and *predicted* (dependent variables), assessing reciprocal relationships within the same analysis (Johnson 1991; Bowen and Guo 2012). Second, this method can simultaneously perform factor analysis and compute regression equations, accommodating regression relationships among different latent variables or among latent and observed variables (Bowen and Guo 2012). General structural equation models contain a measurement model and a structural model. Within the measurement model, multiple observed variables are used to measure latent (unobserved) variables. Within the structural model, the researcher examines the relationships between exogenous and endogenous observed variables and latent factors (Bowen and Guo 2012).

The autoregressive cross-lagged model is derived from the perspective that the current value of a variable is determined by the previous value of that variable (Bollen and Zimmer 2010). Thus, this type of analysis regresses a Time 2 dependent variable on its Time 1 (baseline) measure. Autoregressive cross-lagged models are similar to the examination of residual change score models using OLS regression in that they assess the degree to which baseline (Time 1) independent variables predict a subsequent (Time 2) dependent variable, while controlling for the effects of the dependent variable at baseline (Time 1). But, autoregressive models within an SEM framework have several advantages over the residual change score modeling, including the ability to incorporate multiple indicators into the measurement of a latent variable, the ability to estimate relationships between observed variables and latent factors, and the ability to simultaneously assessing reciprocal effects within a single model (Bowen and Guo 2012; Johnson 1991).

4. Social Network Typologies

The social convoy model has been applied across time and place to study the influences of social ties on mental and physical health. Many studies used a person-centered approach, creating social convoy typologies using quantitative methods such as cluster analysis. While most of these studies solely examined older adults, they have examined different populations and cultures, ranging from studies of the United States, United Kingdom, and Germany, to Israel, China and Japan (Fiori et al. 2008; Fiori et al. 2006; Wenger 1997; Fiori et al. 2007; Litwin 1997; Litwin 1998; Litwin and Landau 2000; Litwin 2001; Litwin and Shiovitz-Ezra 2006; Cheng et al. 2009). What is surprising is that while each study collected data among different populations, created social convoy typologies using different variables, and found varying numbers of convoy types (usually ranging from four to six), four social convoy types were consistently identified: (1) diverse, (2) friend-focused, (3) family-focused and (4) restricted. In addition, some studies found convoy types specific to a certain population. For example, in a comparison of older adults from Detroit and Yokohama, Fiori and colleagues (2008) found a network type unique among the Japanese sample, the "married and distal" type, which was comprised of exclusively married individuals, who reported few close confidants and few network members who lived close by. These authors of this study note that while similar network types may be found across cultures, the types may differ in regards to values on key attributes and on their prevalence across the samples.

A majority of studies using quantitative methods to construct social convoy typologies often used variables such as marital status, parental status, frequency of contact with children/friends, geographic proximity, church attendance and formal/informal group membership as criterion variables for a cluster analysis. But, not all social relationships are positive (Adams and Blieszner 1994), and the social convoy model advocates a definition of social support as characterized by affect, affirmation and aid (Kahn and Antonucci 1980). Thus, other researchers used a more multidimensional approach by incorporating relationship quality, and instrumental and emotional social support into the mix (Fiori et al. 2007; Fiori et al. 2008; Cheng et al. 2009). While a few studies included some variables measuring network structure (e.g., total network size) and/or network composition (e.g., proportion of close others in network, proportion of the network that is geographically close), this study builds on previous literature by measuring network structure and composition using information on respondent reports of close confidants. I use network measures such as *size* (number of network members) and *density* (extent to which members are connected to each other) to measure network structure. I also use measures of network *boundedness* (degree to which they are defined on the basis of traditional kinship) and *gender homogeneity* (extent to which individuals are similar to each other in a network) to measure network composition.

In this chapter, I discuss the close confidant data in depth, as well as reasons for delineating two separate network typologies, one based on network structure and the other on network composition. Next, I discuss the criteria for determining the optimal number of social network types (or clusters) for each typology, the distribution of network characteristics across each network type, and how each network type relates to social and demographic factors of interest. Lastly, I examine the amount of correlation between the network structure and network composition typologies.

4.1 Examining the Close Confidant Data

The Americans' Changing Lives survey asked respondents about information on the size of their network of close confidants, the network density, and the relationship type and gender of their three closest confidants. A minority of Americans' Changing Lives respondents (14.2% or N = 508) reported that they did not have a close confidant, or someone with whom they could share their very private feelings and concerns. Among those without a close confidant, 38% were married in 1986, 78% had one or more children, 23% had two living parents and 26% had either a living mother or father. This illustrates that the mere presence of social relationships, as measured by marital status or parental status, may not be a good indicator of social network (or convoy) ties. Moreover, the major reason for having no close confidants does not appear to be the absence of social relationships.

A majority of the sample (85.8% or N = 3,069) reported anywhere from 1 to 7 close confidants. The respondents who reported at least one close confidant also reported slightly more social relationships compared with those who reported no close confidant. For example, approximately 58% were married, 85% had one or more children, 38% had two living parents and 26% had either a living mother or father. Figures 1-3 depict the close confidant nominations for the sample who reported having at least one close confidant. Figure 1 is for respondents whose first close confidant nomination was a spouse, partner or ex-partner. There are three rows of ovals, with each row representing the relationship type of the first, second and third closest confidant. As portrayed in Figure 1, 31% (N = 965) of individuals who reported at least one close confidant nominated their partner or spouse as their *closest* confidant (their first nomination). Of these individuals, thirty-eight percent only reported one close confidant, their partner/spouse (and thus nominated no one else). Thirty-six percent went on to report a family member as their second closest confidant (second nomination), while 20% reported a friend as their second closest confidant.

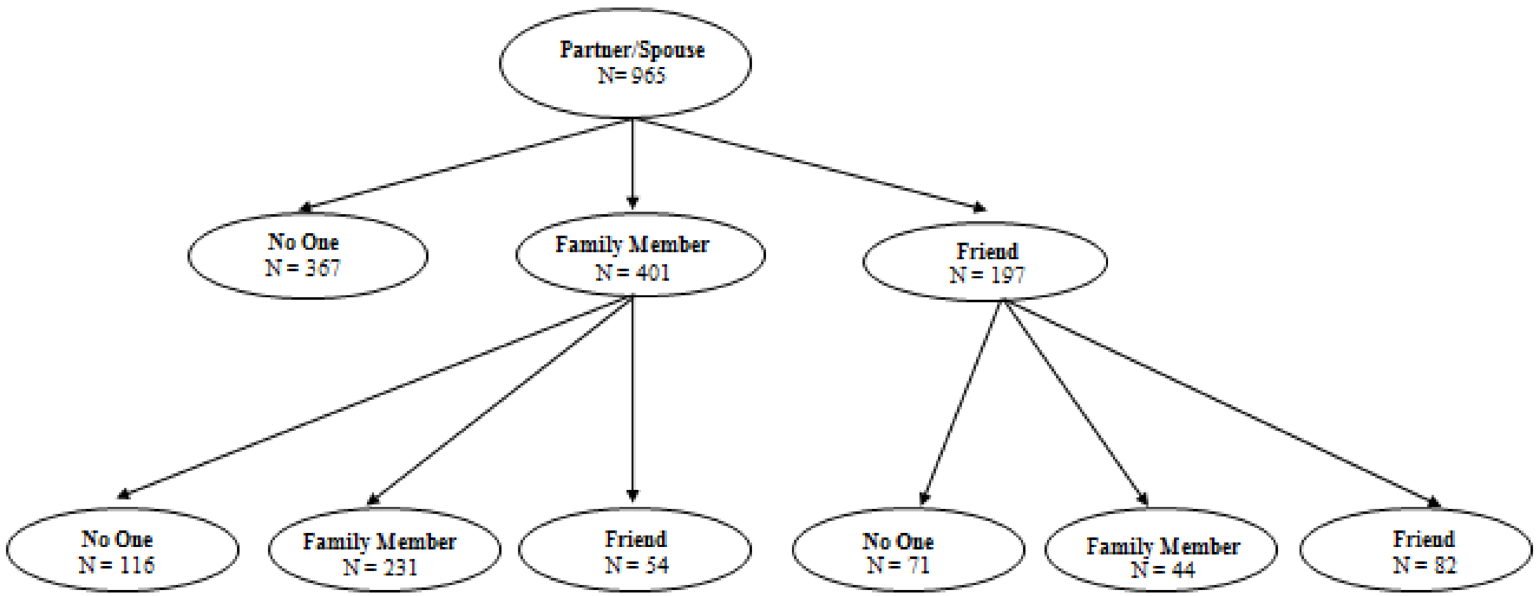

Figure 1: Close Confidant Nominations (1st, 2nd, and 3rd) for ACL Sample Respondents (1986) Whose First Nomination Was A Partner/Spouse.

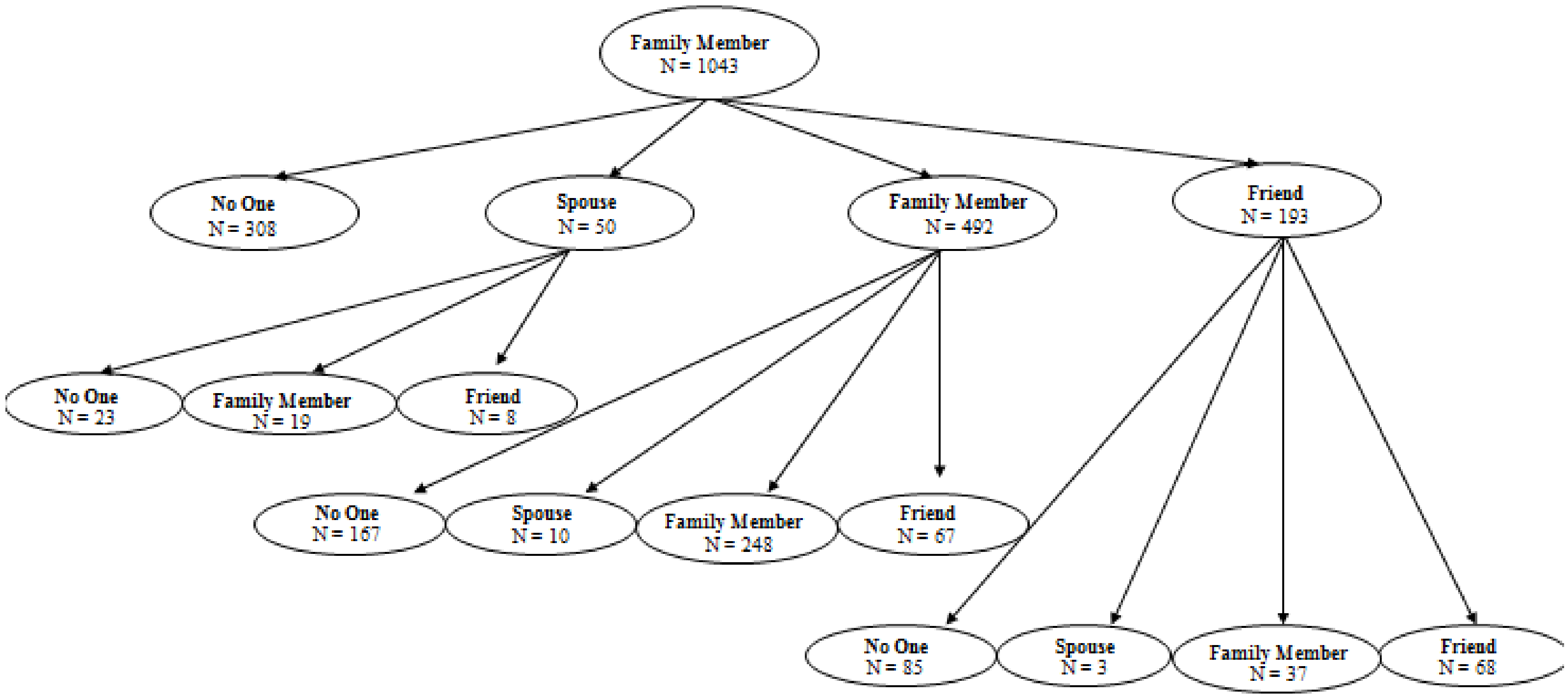

Figure 2: Close Confidant Nominations (1st, 2nd, and 3rd) for ACL Sample (1986) Respondents Whose First Nomination Was A Family Member.

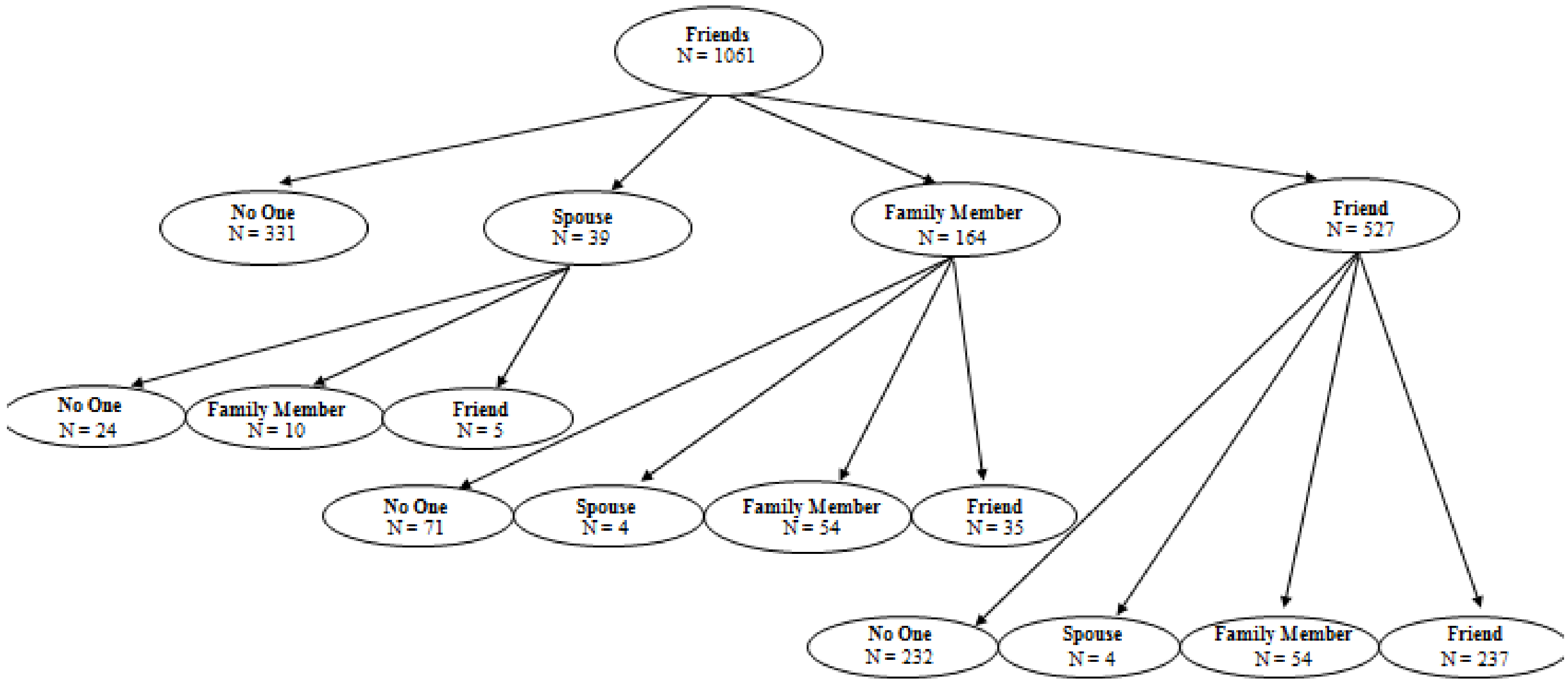

Figure 3: Close Confidant Nominations (1st, 2nd, and 3rd) for ACL Sample (1986) Respondents Whose First Nomination Was A Friend.

Among those who nominated at least one close confidant, Figure 2 portrays the 34% (N = 1043) of individuals whose *closest* confidant (first nomination) was a family member, while Figure 3 portrays the 35% (N = 1061) of individuals whose *closest* confidant was non-kin. An overwhelming majority of non-kin network members were identified as “friends” of the respondents and thus this category is labeled accordingly. A much smaller proportion of non-kin network ties were identified as neighbors, clergy members or priests, and co-workers, business partners or bosses.

In examining Figures 1-3 is it important to note three distinct trends. First, respondents who did not report their spouse or partner as their *closest* confidant (e.g. their first nomination) were not likely to report their spouse as either a second or third nomination. Among the married who reported having at least one close confidant, 51.7% reported their spouse as their closest confidant, 4.5% reported their spouse as their second closest confidant and 1% reported their spouse as their third closest confidant. Thus, close to 43% of married individuals did not nominate their spouse as someone with whom they could share their very private feelings and concerns. Second, an individual whose first nomination was a family member (other than their spouse/partner) was more likely to nominate other family members as second and third nominations. Third, an individual whose first nomination was a friend was also more likely to nominate other friends as second and third nominations. Thus, a large proportion of the sample named only family members or only friends as confidants, with fewer naming a diverse array of relationship types.

4.2. Creating Social Network Typologies

Social network typologies were created from data on respondent reports of close confidants using hierarchical cluster analysis (see Data and Methods). The network structure typology describes characteristics of the actual network, including the size and density of the social ties. The network composition typology describes the social actors within respondents' networks, including the array of relationships that compose the network and the gender composition of the network. The network structure and composition typologies were constructed separately for two reasons. First, while a degree of correlation between the two typologies was expected, structure and composition represent two distinct aspects of the network. Indeed, individuals characterized by the same network composition may differ in regards to their network structure and vice versa. Second, separate network typologies were developed due to the difference in data structure between social network composition (binary) and structure (ordinal/ count/continuous) variables.

The following section discusses the criteria for determining the number of social network types (or clusters) for each typology, describes the distribution of network characteristics for each type, and discusses how each type relates to social and demographic factors of interest. In the last section, I will discuss the amount of correlation between the network structure types and network composition types.

4.2.1 Social Network Structure Typologies Using Hierarchical Cluster Analysis

Hierarchical cluster analysis was applied to the ordinal and count variables representing social network structure. These variables included measures of network size and density. In addition to the aid of a dendogram (or tree diagram), statistics such as the pseudo T squared statistic, pseudo F statistic and cubic clustering criterion (CCC) are helpful in deciding the optimal number of clusters present in the data. The dendogram pointed to either a 4- or 6- cluster solution. The pseudo T squared statistic pointed to a large array of possible cluster solutions, although the results were the strongest for a 4- or 6- cluster solution. Finally, the pseudo F statistic pointed to a 4- cluster solution[1]. Results from the CCC were unclear[2]. As discussed in the Data & Methods section, I evaluated 4-, 5- and 6- cluster solutions and determined that a 4- cluster solution was optimal. This was due to the frequencies of the criterion variables in each cluster and the desire to consolidate the data into the fewest number of clusters while preserving important distinctions in the data.

Table 3 presents the descriptive statistics for the baseline sample by network structure types. The first network structure type is labeled "Small, Dense" because network size is small, with an average of 4 instrumentally supportive and 1.6 emotionally supportive network members. Individuals in the "Small, Dense" network structure type report that, on average, more than half of the network members know each other in the same way that they know the respondent. This structural type represents 44% of the

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[1] In examining the pseudo F statistic, I looked for relatively large values of this statistic. While there are consistently small jumps in the value of the pseudo F statistic as the clusters are joined together, the pseudo F statistic displays a relatively large value compared to prior values at four clusters.

[2] Peaks on the CCC plot with values greater than 2 or 3 indicate good clusters, while peaks between 0 and 2 indicate possible clusters (SAS/STAT User's Guide 2013). For the last 12 clusters formed through hierarchical cluster analysis, the CCC is consistently negative and decreasing, perhaps indicating that the distribution is unimodal or long-tailed.

sample (N = 1565) and is composed of 65% women, 38% Black respondents, and 52% married respondents. This type also reports the oldest age and lowest total annual income.

Table 3: Descriptive Statistics in Means (and Percentages) for Network Structure Types Using Hierarchical Cluster Analysis, ACL 1986 (N = 3,577).

	Small, Dense (N = 1565)	Mixed (N = 900)	Large (N = 494)	Small, Not Dense (N = 618)
Network Structure:				
Network Size (Help/Advise)	4.10	10.55	9.12	3.33
Network Size (Share Feelings)	1.63	1.84	5.54	1.54
Network Density	3.86	3.59	3.62	1.36
Demographic/Background:				
Age	55.11	52.28	54.05	51.05
Female (%)	64.86	57.67	57.69	67.15
Black (%)	37.64	24.78	26.11	34.95
Married (%)	51.57	60.78	60.32	49.84
Total # Children	2.64	2.57	2.79	2.42
Education (Years)	11.00	11.85	11.94	11.87
Income ($)	20,738.02	26,347.22	25,824.90	24,154.53

The next type is labeled “Mixed” because individuals in this cluster reported, on average, having a large number of instrumentally helpful ties (10.55), but few emotionally supportive ties (1.84). In addition, individuals in this cluster reported that more than half of the network members know each other in the same way. This type represents 25% of the sample (N = 900), and is approximately 58% women, 25% Black respondents and 61% married respondents. This network type reports the highest total annual income, on average.

The third structural type is labeled “Large” because respondents report, on average, large numbers of both instrumentally helpful (9.12) and emotionally supportive (5.54) network ties and, again, more than half of the network ties know each other in the same way that they know the respondent. This group represents 14% of the sample (N = 494), and is composed of 58% women, 26% Black respondents and 60% married respondents.

The last structural type is labeled “Small, Not Dense” because respondents in this group report the fewest number of instrumentally helpful ties (3.33), and the fewest number of emotionally helpful ties (1.54), with the network characterized by a low degree of density (almost none of the network ties know each other in the same way that they know the respondent). The “Small, Not Dense” type represents 17% of the sample (N = 618). Approximately 67% of respondents in this network type are women, 35% are Black, 50% are married and they reported the lowest age, on average.

For the 14% of the sample who did not report having a close confidant, these individuals may be classified in either the “Small, Dense,” “Large,” or “Small, Not Dense” structure types. While these respondents report no close confidants (and hence are coded as having 0 close confidants), they still report the number of instrumentally helpful friends and relatives, as well as how close these other network members are to each other. They will not be classified in the “Mixed” structure type, which is characterized by having a large number of close confidants and instrumentally helpful ties.

4.2.2 Social Network Composition Typologies Using Hierarchical Cluster Analysis

Hierarchical cluster analysis was applied to the binary variables representing social network composition. The network composition variables represent the relationship types (whether an individual nominated a spouse/partner, a family member, and/or a friend) and gender composition (all women, all men, or mixed gender) of close confidant nominations. In addition to the aid of a dendogram (or tree diagram), statistics such as the pseudo T squared and pseudo F are helpful in deciding the optimal number of clusters present in the data (the cubic clustering criterion, CCC, cannot be computed for distance data). Inspection of the dendogram pointed to a 3-, 4- or 7 cluster solution while inspection of the pseudo T squared statistic pointed to a 4- or 7- cluster solution. A 7-cluster solution was chosen because of the frequency of the criterion variables in each cluster and the desire to preserve important distinctions in the data.

The seven network composition clusters are displayed in Table 4, along with the descriptive statistics for each cluster. The first network composition type is labeled “Female Friend” because all of the members nominated at least one friend as a close confidant and all close confidants were reported to be female. This group represents 12% of the sample (N = 430) and respondents in this group are primarily women (88%). In addition, 38% of group members self-identify as Black/Africa-American, 42% are married, and they report an average of 2.7 children.

Table 4: Descriptive Statistics, in Means (and Percentages) for Network Composition Types Using Hierarchical Cluster Analysis, ACL 1986 (N = 3,577).

	Female Friend (N = 430)	Female Family (N = 634)	Family + Spouse (N = 535)	Restricted (N = 507)	Diverse (N = 728)	Male-Focused (N = 436)	Female Spouse (N = 307)
Network Composition:							
Relationship Types:							
Spouse/ Partner (%)	0.00	0.00	59.63	0.00	40.66	35.09	100.00
Family Member (%)	0.00	100.00	100.00	0.00	48.08	31.19	19.87
Friends (%)	100.00	33.28	0.00	0.00	99.86	46.33	3.26
Ties by Gender:							
All Female (%)	100.00	100.00	0.00	0.00	0.00	0.00	100.00
All Male (%)	0.00	0.00	0.00	0.00	0.00	100.00	0.00
Male & Female (%)	0.00	0.00	100.00	0.00	100.00	0.00	0.00
Demographic:							
Age	55.58	57.34	56.99	55.78	46.66	52.60	50.88
Female (%)	87.91	89.43	61.87	57.59	56.87	57.57	0.33
Black (%)	37.67	43.06	23.55	35.31	30.22	30.05	21.50
Married (%)	42.09	42.59	67.10	38.26	52.34	66.28	93.16
Total # Children	2.70	2.66	2.79	2.59	2.20	2.79	2.80
Education (Years)	11.13	10.75	11.50	10.82	12.65	11.47	11.95
Income ($)	20,069.77	17,981.07	23,364.49	19,018.74	28,667.58	23,939.22	33,786.64

The next group is labeled “Female Family” because all members nominated at least one family member as a close confidant, while approximately 1/3 also nominated at least one friend, and all reported close confidants were female. This group represents 18% of the sample (N = 634), is composed primarily of women, slightly under half of members report being married, and has slightly lower average levels of education and income than any other group. The “Female Family” type has the largest proportion of Black/African-American respondents (43%). This corresponds with research that shows, among blacks, family members are more common as members of social networks than non-family members (Oliver 1988).

The next group is labeled “Family + Spouse” because all members nominated at least one family member, while almost 60% also nominated a spouse/partner. The network composition of this group is mixed in terms of gender, with all respondents naming at least one woman and one man as a close confidant. This group represents 15% (N = 535) of the sample. Compared to the previous two groups, respondents in this group are more likely to be men, more likely to be married and less likely to identify as Black/African-American. This group also reports slightly higher levels of education and income than the previous two groups.

The fourth group is labeled “Restricted” and is composed of respondents who did not nominate any close confidants. These individuals form their own network composition type because the variables used in this cluster analysis were generated only from information obtained on reported close confidants. This group represents 14% of the sample (N = 507).

The fifth group is labeled “Diverse” because, although almost all individuals nominated at least one friend as a close confidant, 41% nominated a spouse/partner and 48% nominated a family member. The gender composition for this cluster is mixed. This group represents 20% of the sample (N = 728) and is the largest network composition cluster. Compared with other composition types, respondents in this group are younger and report the fewest number of children and most years of education, on average. Approximately 58% of individuals in this composition type are women, 35% are Black and 38% are currently married at the time of the baseline survey.

The sixth group is labeled “Male-Focused” because it is the only group where individuals’ nominations were composed solely of men. This group represents 12% of the sample (N = 436), and is composed of 58% women, 30% Black respondents and 66% married respondents.

Lastly, the group labeled “Female Spouse” contains individuals who all nominated a spouse/partner as a close confidant, while 20% nominated at least one family member and 3% nominated at least one friend. All close confidants who were reported were identified as being female. This group is composed *mostly* of married men whose only nomination was their spouse; only a few also nominated a family member and/or friend. It is not surprising to find a social network composed primarily of a female spouse/ partner. Research by Antonucci and Akiyama (1987) finds that men are significantly more likely than women to report relying on their spouses, as opposed to children and friends, for numerous types of emotional support (e.g., confiding in, reassurance, talking to when upset). This last group was least likely to identify as being

Black, and has relatively high levels of educational attainment and total family income compared to other groups.

4.2.3 Correlation between the Network Structure and Composition Typologies

In this section, I examine the extent of correlation between the network structure and network composition typologies. While I expect that the typologies will be correlated somewhat, too much overlap between them may suggest possible multicollinearity in upcoming analyses, where both typologies will be included in regression models to predict an array of health indicators. Thus, too much correlation between the two typologies may mean only one typology will be used in upcoming analyses to predict health, or the two typologies should be combined to form a single typology.

Before examining the cross-tabulation of network typologies, I hypothesize certain correlations between network composition and structure. First, individuals who have family-focused network compositions may also predominately have network structures characterized by a high degree of network density. Second, individuals characterized as having a "Restricted" network composition may belong to smaller networks. It is unclear whether being in a "Restricted" network is also correlated with network density.

Table 5 portrays the cross-tabulation of network structure types and composition types. The contingency coefficient is a measure of association based on Chi-Square and is used for nominal variables, where 0 indicates no association between the rows and columns of the contingency table, while 1 indicates a high degree of association. The contingency coefficient for this table is equal to 0.3292, indicating some degree of association between the network structure and composition typologies[3]. As hypothesized above, individuals who have family-focused network compositions also predominantly have network structures characterized by a high degree of network density. As portrayed in Table 5, those in the “Female-Family” and “Family + Spouse” composition types are more likely to have networks characterized by high network density. Therefore, these family-focused individuals are less likely to belong to a “Small, Not Dense” network and more likely to belong to a network characterized by a higher degree of density (“Small, Dense,” “Large,” or “Mixed”). In addition, those in the “Female Spouse” composition type are most likely to have a “Small, Dense” network structure, followed by a “Mixed” network structure. This is not surprising considering this group is composed of mostly married men who nominate a spouse or partner as their only close confidant.

Table 5: Cross-Tabulation (in Frequencies) of Network Composition Types and Network Structure Types, ACL 1986 (N = 3,577).

		Network Structure				
		Small, Dense	Mixed	Large	Small, Not Dense	Totals
Network Composition	Female Friend	187	98	32	113	430
	Female Family	306	159	80	89	634
	Family + Spouse	226	126	158	25	535
	Restricted	246	108	0	153	507
	Diverse	242	185	178	123	728
	Male-Focused	208	126	30	72	436
	Female Spouse	150	98	16	43	307
	Totals	1,565	900	494	618	3,577

In accordance with the second hypothesis, individuals in the restricted network belong to small networks, but these networks may have either high or low degrees of

[3] Additional measures of association include the Phi Coefficient (0.3486) and Cramer’s V (0.2013).

network density. No individual in the “Restricted” composition type belongs to a “Large” network, which here is characterized by a large number of both close confidants and instrumentally supportive social ties. Instead, these individuals are scattered across the “Small, Dense”, “Mixed” and “Small, Not Dense” structure types, each with varying degrees of density but none of which are characterized by many close confidants.

Lastly, individuals in “Male-Focused” composition types are more likely to be in “Small, Dense” and “Mixed” network structures, while those in “Female-Friend” composition types are least likely to be in “Large” network structures. Those in the “Diverse” composition type are fairly evenly scattered across the four network structure types. While the above-mentioned trends are apparent in Table 5, all except one of the cells in the contingency table contain cases. Thus, classification into a network structure type does not translate into classification into a specific network composition, and vice versa. In the next chapter, possible problems of multicollinearity will be addressed and tested in the regression models to be presented.

4.3 Conclusions

This study used data on respondent reports of close confidants to develop social convoy typologies characterizing network structure and network composition. The network structure types include “Small, Dense,” “Mixed,” “Large,” and “Small, Not Dense.” Interestingly, while there are small network types with different levels of density (i.e., “Small, Dense” and “Small, Not Dense”), the “Mixed” and “Large” types are characterized by medium to high levels of density. No clusters have a large number of network members with low density, where most members do not know each other in the same way.

Across previous studies of social convoys, four similar social convoy types have been found. These types have been labeled diverse, friend-focused, family-focused and restricted. In this study, I found similar social composition types, including “Diverse,” “Restricted,” “Family + Spouse,” “Female-Family,” and “Female-Friend” compositions. The family- and friend-focused types in this study are preceded by the adjective “female” because the close confidants are reported to be all women. Many previous studies of social convoys did not take gender composition into account, but it is possible that those social convoys were composed primarily of women as well. According to the data used in this study, a large majority of close confidants were women. Among respondents who named a primary close confidant, 67% of the nominations were for women. Among respondents who named a second and/or third close confidant, 64% and 62% of the nominations were for women, respectively. The current results also point to two additional composition types: “Male-Focused” and “Female-Spouse” types. The “Male-Focused” type stands out because it is the only network composition type where all close confidants were reported to be men. The “Female-Spouse” type is composed of mostly married men who name their spouse/partner as their primary close confidant.

The next steps will be to examine the predictive value of the social network types on an array of mental and physical health indicators, both in the cross-section and over time.

5. Social Network Typologies and Health

Using large-scale community studies, social epidemiologists have consistently shown that a lack of social network ties predicts mortality (Berkman and Syme 1979; House et al. 1982; Schoenbach et al. 1986; Orth-Gomér and Johnson 1987; Seeman et al. 1987; Pinquart and Duberstein 2010). While termed social ties or social networks, interpretation of the measures used in this early research has been debated in the social sciences. These studies rarely use standard network concepts, measures or analyses for the assessment of network size, strength or composition. Conversely, social networks have been inferred from variables such as marital status, contact with children and friends, church attendance and informal/formal group membership (Berkman and Glass 2000).

Social network methods help researchers study social ties that may cut across traditional kinship, residential or class-based groups. This is essential because network structure does not always conform to our preconceived notions of what constitutes a community, which usually are defined on the basis of geographic boundaries or kinship (Berkman and Glass 2000; Wellman 1988). Unfortunately, many health researchers continue to use variables to infer network structure, while others focus on the role of social support on health to the neglect of the social structures from which the support comes (Berkman and Glass 2000).

Network structure and composition are important in shaping health through the provision of social support, access to material resources, social influence, social engagement and attachment (Berkman and Glass 2000). Similar to other social structures, networks can be a source of opportunities as well as constraints on individual behavior. A few early health researchers examined the association of a number of network characteristics, such as size, density, homogeneity, directedness, geographical distance, duration and frequency of contact on health. Gallo (1982) found significant positive correlations between a composite measure of health status and network size, density, homogeneity and directedness among a sample of older adults. Network size had a moderate, positive association with health status, meaning that larger networks were associated with better health status, a similar finding to that reported by earlier epidemiologists. Individuals in more dense social networks also reported better health. Network homogeneity – in terms of age, sex, marital status, occupation and ethnicity – had a slight, positive association with health, where high levels of homogeneity were associated with slightly better health status. Lastly, regarding directedness of the relationship, in networks where both the respondent and network members initiated contact, respondents reported better health. But, in networks where the network members were the ones who initiated contact with the respondent, the respondent reported worse health. This is possibly a result of social selection, where sick individuals are unable to initiate contact with their network members. In contrast to Gallo's study, Israel and Antonucci (1987) did not find statistically significant associations between mental health and network size or density.

Kahn and Antonucci's (1980) social convoy model refocuses this scholarship by emphasizing how the giving and receiving of social support is embedded within a network of social ties that changes across the life course. The social convoy model integrates social network analysis into health research, while also drawing from tenets of the life-course perspective by calling for the longitudinal study of social networks and health over the life course. As previously discussed, many health researchers created typologies of social convoys, assessing the relationships of these typologies with various indicators of health and well-being. Compared to restricted networks, more diverse social convoy types typically have been associated with increased and more recent healthcare utilization (Litwin 1997), higher morale (Litwin 2001), higher levels of well-being, life satisfaction (Fiori et al. 2007; Cheng et al. 2009), increased probability of survival (Litwin and Shiovitz-Ezra 2006; Fiori et al. 2008), lower morbidity (Litwin 1998; Fiori et al. 2007), and fewer depressive symptoms (Fiori et al. 2006; Fiori et al. 2007; Cheng et al. 2009). Results regarding the health benefit of friend-focused and family-focused convoy types remain mixed (Cheng et al. 2009; Litwin and Landau 2000; Litwin and Shiovitz-Ezra 2006; Litwin 1997; Fiori et al. 2006; Fiori et al. 2007). It was only in one study, using a community-based sample of older adults in Yokohama, Japan, that researchers did not find a relationship between social network type and measures of mental or physical health (Fiori et al. 2008).

Many of the above-mentioned studies are cross-sectional, examining the association between social convoy types and health at one point in time. While informative, cross-sectional studies cannot distinguish whether the association between social convoys and health is due to social causation (social convoys affect health) or social selection (health status affects social convoys). Longitudinal data and analyses are needed to parse out whether the network – health association is due to social causation, or social selection, or possibly both. Moreover, longitudinal data and methods are also needed to study how social networks change as individuals' age, how mental and physical health change as individuals' age, and the possible dynamic interplay between the two over time. While this current chapter tests social causation hypotheses, the third and final empirical chapter simultaneously evaluates both social causation and selection hypotheses.

This chapter addresses a number of methodological and substantive research questions. First, what are the relationships between social network structure and composition and health? To address this question, I will examine the cross-sectional associations of network structure and composition types developed in the preceding chapter with a number of health indicators, which include self-rated health, psychological distress, and self-esteem. Second, do the cross-sectional associations between networks and health differ by age, gender or race? To address this question, I examine age (< 60 vs. 60+), gender (women vs. men) and race (black vs. other) as potential moderators of the associations between networks and health. Third, are the associations between social networks and health due to social causation, namely, do social networks have a direct effect on health over time? To address this question, I will use network structure and composition types (as measured at baseline) to predict self-rated health, psychological distress and self-esteem at Wave 2 (1989) and at Wave 3 (1994), while controlling for the effects of baseline health measures. Lastly, the construction of social convoy typologies represents what has been referred to as a "person-centered" approach. The person-centered approach, as embodied by typologies, will be compared with the variable-centered approach in predicting health indicators, at baseline and over time. This will allow me to assess the utility of creating and using typologies to study the influence of social networks on health.

5.1 Cross-Sectional Associations: Social Network Typologies and Health

5.1.1 Hypotheses

Hypotheses for how the network structure and composition types will relate to various indicators of health can be generated from past variable- and person-centered research. As previously discussed, what is termed “variable-centered” research focuses on how specific variables relate to health, while “person-centered” research focuses on the development of typologies and how these typologies relate to health.

As supported by much previous literature, larger social networks are more beneficial for mental and physical health than smaller networks, with this relationship perhaps due to having *more sources* of social support, assistance, advice and aid. Second, while there is a dearth of research on this issue, it appears that network density can influence health in one of two ways. Denser networks may represent strong, durable structures of closeness and intimacy. Since members know each other in the same (or similar) way, they can effectively work together to provide optimal support, care and help. Indeed, coordination and organization of a dense network may be as simple as a few phone calls (Adams and Blieszner 1995). This is supported by research from Gallo (1982), who found a slight positive association between physical health status and network density. Conversely, denser networks contain fewer weak or bridge ties, thus limiting the availability of information, skills and resources within a network (Granovetter 1973; Burt 2004). Indeed, social selection processes may also be at work, whereby younger, healthier individuals are more able to bridge structural holes (Cornwell

2009a; Cornwell 2009b) and maintain social networks that have a low degree of density. Thus, in considering the health benefit of the social *structure* types, I hypothesize that the "Large" network type will be the most beneficial for all indicators of health due to the large number of instrumentally and emotionally supportive network ties and the moderately high degree of density. This will be followed by the "Mixed" social network type. Due to the dearth of research on network density and health, I am unable to hypothesize whether "Small, Dense" or "Small, Less Dense" networks will be more beneficial for physical and mental health.

Much of the social convoy literature suggests that diverse social convoys are most beneficial for a variety of health measures, although some indicate that certain friend-focused and family-focused types also confer health benefits. In accordance with Weiss' (1969) theory of the functional specificity of relationships, more diverse networks containing a greater number of relationship types will be better for mental and physical health because each type of relationship may serve a specific function. Therefore, the more relationship types present in a social network, the more functions that are fulfilled. Thus, regarding the network *composition* types, I hypothesize that belonging to the "Diverse" type will confer the greatest mental and physical health advantage. I also hypothesize that networks composed of family (i.e., "Female Family," "Family + Spouse," "Female Spouse") and friends (i.e., "Female Friend") will be more beneficial for mental and physical health than the "Restricted" network. In particular, parents, children and siblings provide more financial aid, emotional support and instrumental support than friends, especially when a person's needs are significant and chronic (Wellman and Wortley 1990; Adams and Blieszner 1995) . But, the presence of friends has been shown to be more important for psychological well-being than the presence of family. It is possible this is due to the achieved vs. ascribed status distinction, but friendship may also have a strong effect on well-being because it is a primarily source of companionship. People enjoy spending time with, engaging in leisure activities with, and having frequent contact with their friends (Antonucci and Akiyama 1995). Thus, it is also possible that membership in family-oriented networks confers more physical health benefits, but membership in friend-oriented networks confers more mental health benefits. Lastly, women are most likely to be named as a close confidant by both women and men. While no research study has examined respondents' perceptions/evaluations of female and male network members, women tend to report higher relationship quality, higher relationship satisfaction, and more frequent interaction from their social networks (Adams and Blieszner 1995). Thus, I hypothesize that social networks composed of more women will be better for mental and physical health than social networks composed of mostly men. Thus, while membership in the "Male-Focused" network may be better for health than membership in the "Restricted" network, it will be worse for health than all other networks types, which contain at least some or all women.

5.1.2 Poor/Fair Self-Rated Health

Table 6 presents the parameter estimates from the regressions of all three dependent variables on network structure and composition types. The unweighted and weighted results were similar, so the unweighted results are presented in this chapter. (For tables containing the weighted results, as well as all nested models, see Appendices A – G). As would be expected, age is positively associated with reports of poor/fair self-rated health, and educational attainment and income are negatively associated with reports of poor/fair self-rated health. Interestingly, being married was significantly associated with reports of poor/fair self-rated health, but this was true only after inclusion of income into the model. No network structure types were significantly associated with poor/fair health. Regarding network composition types, while all parameters estimates are negative, as hypothesized, only having a “Male-Focused” network composition is significantly associated with a lower likelihood of reporting poor/fair health. This is counter to the above-mentioned hypotheses, where I predicted that membership in a “Male-Focused” network would more beneficial for health than membership in a “Restricted” network, but less beneficial for health than membership in a network characterized by all women or a mixed gender composition. Lastly, having “Family + Spouse” or “Female Spouse” network compositions are weakly associated with self-rated health.

Table 6: Regression of Poor Self-Rated Health, Depressive Symptom Count and High Self-Esteem on Social Network Typologies, ACL 1986 (N = 3,577), Not Weighted

	POOR SRH	DEP	HIGH SE
Background Factors:			
Age	0.023***	-0.008***	0.018***
Female	-0.083	0.054†	-0.202†
Black	0.157	0.060*	0.224*
Married	0.248*	-0.082*	-0.171
Children (Total #)	0.031	0.002	0.002
High School	-0.623***	-0.151***	0.190
> High School	-0.511***	-0.164***	0.337*
Income (Logged)	-0.595***	-0.117***	0.446***
Network Structure [1]			
Small	-0.017	-0.045	-0.035
Mixed	-0.201	-0.220***	0.357*
Large	0.025	-0.190***	0.514**
Network Composition [2]			
Diverse	-0.226	-0.129**	0.331*
Female Family	-0.154	-0.114*	0.149
Family + Spouse	-0.282†	-0.167**	0.433*
Female Spouse	-0.423†	-0.351***	0.541*
Female Friends	-0.118	-0.032	-0.018
Male-Focused	-0.386*	-0.159**	0.341†
Intercept	3.363	3.192	-4.015
AIC	3246.34	17131.72	3212.14
-2 Log Likelihood (BIC)	3210.34	(17249.18)	3176.14

*** $p < 0.001$ ** $p < 0.01$ *$p < 0.05$ † $p < 0.10$

Notes: [1] Reference group is 'Small, Not Dense'

[2] Reference group is 'Restricted'

5.1.3 Count of Depressive Symptoms

The relationships between network typologies and mental health are much stronger than those for self-rated health. As expected, age, being married, educational attainment and income are negatively associated with counts of depressive symptoms, while being a woman and being Black have a weak, positive association with counts of depressive symptoms. Belonging to a social network with a “Large” or “Mixed” structure is associated with fewer reported depressive symptoms. It appears that size, and not network density, is most predictive of depressive symptoms. Those in the “Small, Dense” network structure have a similar network size, but higher network density, than those in the “Small, Not Dense” network but there does not appear to be any significant difference between the two types in regards to counts of depressive symptoms. Lastly, as expected, the parameter estimates for all network composition types are negative when compared with the “Restricted” composition type. “Female Spouse” has the strongest protective effect on depressive symptoms, followed by the “Family + Spouse,” “Male-Focused,” “Diverse,” and “Female Family” types. Having a network composed primarily of female friends does not appear to be protective against depressive symptoms.

5.1.4 High Self-Esteem

Age, being Black, educational attainment and income are positively associated with reporting high self-esteem, while being a woman has a weak negative effect. As predicted, having a “Large” or “Mixed” network structure is positively associated with high self-esteem, while having a “Small, Dense” structure appears no different than having a “Small, Not Dense” structure. This is similar to the results reported above for counts of depressive symptoms, and it again appears that it is network size that is driving this association. Lastly, most of the parameter estimates for network composition type are in the expected positive association. Individuals in networks characterized by “Female Spouse,” “Family + Spouse,” or “Diverse” compositions are significantly more likely to report high self-esteem compared to those in a ‘Restricted’ network. While membership in a “Male-focused” network is weakly associated with high self-esteem, there is no difference in self-esteem between those in a “Female Family,” “Female Friends,” or

"Restricted" network. Individuals in these network composition types appear to be very similar to each other in regards to reporting high self-esteem.

5.1.5 Person-Centered vs. Variable-Centered Approach

As previously discussed, variable-centered approaches have been used to examine the effects of certain variables – such as marital status, parental status, frequency of contact with children and friends, religious involvement and formal/informal group membership -- on health outcomes of interest. Composite measures, even those that weight some variables more heavily than others, are considered variable-centered. These composite measures simply attempt to sum up respondents' social networks using a scale of low to high. But, while examining the isolated effects of these variables on health may be informative, individuals are embedded in social networks with an array of attributes (Fiori, et al. 2008). Person-centered approaches differ from variable-centered approaches in that many use data-driven clustering methods to create social network typologies. These typologies represent the constellation of an individual's social network attributes and reflect the complex, multidimensional, and aggregate nature of social life (Fiori et al. 2006).

What is the benefit of using a person-centered approach to measuring social networks? Is a variable-centered approach just as or even more informative when predicting mental and/or physical health? Table 7 presents the results from analyses using a variable-centered approach using the baseline sample. Here, the survey variables used to create the social network typologies are now used as independent variables in regression analyses predicting mental and physical health outcomes. What is apparent across the three columns of Table 7 is that the size of the social network providing instrumental support (advice and help) has strong relationships with all of our dependent variables – poor/fair self-rated health, counts of depressive symptoms and high self-esteem. The size of the network providing emotional support (i.e., close confidants) is associated with high self-esteem, and only weakly associated with counts of depressive symptoms. Very few of the variables representing network composition provide much help in predicting any of the dependent variables. Individuals who nominated only male close confidants were less likely to report poor/fair self-rated health, while gender composition of close confidants is weakly associated with depressive symptom counts, at best. Lastly, those who nominated their spouse/partner as a close confidant exhibited fewer symptoms of depression than those who did not nominate a spouse/partner.

Table 7: Regression of Poor Self-Rated Health, Depressive Symptom Count and High Self-Esteem on Social Network Variables, ACL 1986 (N = 3577), Not Weighted.

	POOR SRH	DEP	HIGH SE
Background Factors:			
Age	0.024***	-0.007***	0.017***
Female	-0.020	0.097***	-0.273**
Black	0.159	0.047	0.252*
Married	0.204†	-0.061†	-0.194†
Children (Total #)	0.032	0.001	0.003
High School	-0.623***	-0.144***	0.175
> High School	-0.526***	-0.160***	0.321*
Income (Logged)	-0.591***	-0.109***	0.431***
Network Structure			
Network Size (Help/Advise)	-0.035***	-0.029***	0.053***
Network Size (Share Feelings)	0.012	-0.019†	0.099*
Network Density	-0.040	-0.015	-0.020
Network Composition			
Spouse Nom	0.097	-0.107*	0.120
Family Nom	0.012	0.002	-0.106
Friend Nom	0.086	0.054	-0.200
All Female Noms	-0.220	-0.094†	0.119
All Male Noms	-0.417*	-0.111†	0.276
Mixed Gender Noms	-0.260	-0.044	0.217
Intercept	3.476	3.195	-3.943
AIC	3241.44	17110.02	3208.44
-2 Log Likelihood (BIC)	3205.44	(17227.48)	3172.44

*** $p < 0.001$ ** $p < 0.01$ *$p < 0.05$ † $p < 0.10$

Thus, I argue that while variable-centered approaches have been informative in health research, the use of person-centered approaches allows for a more nuanced understanding of how individuals are embedded in networks with an array of attributes, and the extent to which these networks affect mental and physical health. The variable-centered approach presented in Table 7 reinforces the fact that larger social networks are beneficial for mental and physical health, which is also apparent in the person-centered approach in Table 6. In addition, while the variable-centered approach may lead us to believe that network composition is only weakly associated with mental health at best, the person-centered approach convincingly portrays how individuals' constellation of network members impact both positive and negative aspects of mental health.

5.1.6 Age, Gender and Race as Potential Moderators

Many of the early epidemiological studies examining the influence of social ties on mortality established that age, gender and race were important moderators in this relationship. Thus, models predicting the three dependent variables were stratified by age (> 60 vs. 60+), gender (women vs. men) and race (Black vs. other) to ascertain if these were potentially important moderators in the social networks-health connection (See Tables I – K in the Appendix). Where, upon visual inspection, there appeared to be substantial differences between groups, interaction terms were tested for statistical significance using the pooled baseline sample. Each interaction term was tested separately because the evaluation of three potential moderators, as well as presence of nine binary variables representing network structure and composition types, translated into a large number of potential interactions terms, all of which could not be entered into the same model.

In stratifying the analyses by age, gender and race it appeared as if some of the associations between network type and health were of a stronger magnitude or statistically significant for some groups, while not for others. Only two interaction terms were statistically significant at the $p < 0.05$ level. In predicting counts of depressive symptoms, there is a statistically significant interaction between race and having a "Male-Focused" network composition. While having a "Male-Focused" network is protective against depressive symptoms for other racial groups, it is not protective against depressive symptoms for Black respondents. Lastly, in predicting high self-esteem, there is a statistically significant interaction between gender and having a “Mixed” network structure. Having a “Mixed” network structure -- which includes a large number of instrumentally helpful ties, but a small number of close confidants – promotes high self-esteem for men but not for women.

5.2 Predicting Changes in Health over Time

In order to determine social causation, researchers must go beyond demonstrating a mere correlation between an independent (X) and dependent (Y) variable. They must demonstrate temporality in order to make a strong claim for causal inference, showing that the independent (X) variable of interest precedes the dependent (Y) variable in time. Longitudinal data is needed to provide support in a claim for causality. Thus far, I have shown that there are strong cross-sectional relationships between the social network types developed in Chapter 3 and three indicators of health (although the relationships were strongest for mental health than for physical health). In addition, to help rule out spuriousness, potential confounders were controlled for in these cross-sectional analyses. There are strong theoretical reasons to argue that the cross-sectional relationships between network structure and composition types and health are due to social causation (i.e., network structure or composition affecting health). But, these associations may be due to social selection, whereby physically and mentally healthy individuals select into certain social networks, for instance, larger networks with a more diverse array of members. Therefore, longitudinal data will be used to determine whether membership in social network typologies as measured at baseline affects mental and physical health at Wave 2 (1986) and at Wave 3 (1994).

This section presents findings from studying change over time using residualized change scores (also known as the regressor variable method), although results using change scores are reported in the Appendices (M – O). The aim of these analyses is to examine the relationships between a set of independent variables and a dependent variable, $Y_{2,}$ while controlling for the effects of Y_1. Here, Y_1 and Y_2 are measurements of the same variable at two different points in time. This method of studying change essentially treats the Y_1 variable as a control variable (Allison 1990). Thus, ordinary least squares (OLS) regression was used to regress self-rated health, psychological distress and self-esteem, measured as continuous variables at W2 and W3, onto the network structure and composition types while controlling for the effect of that particular health indicator at baseline (W1). (For unweighted and weighted results using the change score method, see Appendices M-O).

5.2.1 Hypotheses

The hypotheses proposed here are similar to those stated above in regards to the cross-sectional analysis, although they refer to changes in mental or physical health over time. In regards to the network structure typology, membership in a "Large" or "Mixed" network will predict better self-rated health and self-esteem and lower psychological distress over time than membership in either a "Small, Dense" or "Small, Not Dense" network. I also hypothesize that it is the size of the social network which will influence mental and physical health over time, with membership in a "Small, Dense" network having a similar influence on self-rated health, self-esteem and psychological distress over time as membership in a “Small, Not Dense” network.

In regards to the social composition typologies, I hypothesize that membership in a “Diverse” network will be most beneficial to mental and physical health over time, followed by membership in networks composed of family (i.e., “Female Family,” “Family + Spouse,” and “Female Spouse”) and friends (i.e., “Female Friend”). Compared to membership in a “Restricted” network, these network types will predict increases in self-rated health and self-esteem and decreases in psychological distress over time. Lastly, I predict that membership in a “Male-Focused” network will be more beneficial for health than membership in a “Restricted” network, but less beneficial for health over time than membership in other networks composed of both men and women or mostly women.

5.2.2 Self-Rated Health

Table 8 shows the distribution of change (in standard deviation from the baseline measure) for self-rated health, psychological distress and self-esteem over time, between Wave 1 (1986) - Wave 2 (1989) and Wave 1 (1986) – Wave 3 (1994). The most striking finding in Table 8 is that most of the sample changes very little over time in regards to these health measures. In the three years between Wave 1 to Wave 2, 88%, 62% and 67% of the sample changed less than 1 standard deviation from their baseline measure of self-rated health, psychological distress and self-esteem, respectively. Similar results can be seen when examining changes in mental and physical health over the eight years from Wave 1 to Wave 3.

Table 8: Distribution of Changes in Mental and Physical Health Measures, ACL 1986, 1989, 1994.

	Change W1 to W2 (N = 2,812)		Change W1 to W3 (N = 2,360)	
	Count (#)	Percent (%)	Count (#)	Percent (%)
Self-Rated Health:				
Increase 2+ SD	10	0.36	18	0.76
Increase 1 SD	107	3.81	77	3.26
No Change	2471	87.87	2034	86.19
Decrease 1 SD	178	6.33	192	8.14
Decrease 2+ SD	46	1.64	39	1.65
Psychological Distress:				
Increase 2+ SD	169	6.00	54	2.27
Increase 1 SD	709	25.21	207	8.77
No Change	1733	61.61	1663	70.46
Decrease 1 SD	156	5.54	346	14.68
Decrease 2+ SD	46	1.64	90	3.82
Self-Esteem:				
Increase 2+ SD	110	3.93	102	4.31
Increase 1 SD	384	13.66	370	15.66
No Change	1874	66.63	1500	63.57
Decrease 1 SD	347	12.33	306	12.98
Decrease 2+ SD	97	3.46	82	3.47

The first and fourth columns in Table 9 present the parameter estimates for the OLS regression of self-rated health measured at Wave 2 and Wave 3 on social network typologies, while controlling for the effects of self-rated health measured at baseline. The unweighted and weighted results were similar, and so the unweighted results are presented in this chapter. (For tables containing the weighted results, see Appendix L). While age and being female negatively predict increases in self-rated health between Waves 1 and 2, education and income positively predict increases in self-rated health between Waves 1 and 2. The binary variables representing network structure and composition do not predict self-rated health between Waves 1 and 2. Similar results are seen in Table 9 for models predicting self-rated health measured at Wave 3.

Table 9: Regression of Self-Rated Health, Psychological Distress and Self-Esteem on Social Network Variables, ACL 1989 and 1994, Not Weighted.

	Wave 2 (N = 2,812)			Wave 3 (N = 2,360)		
	SRH	**DEP**	**SE**	**SRH**	**DEP**	**SE**
Background Factors:						
Age	-0.004***	-0.011**	0.001	-0.001	-0.004	-0.011***
Female	-0.081*	0.049	-0.139†	0.006	-0.158	-0.115
Black	-0.016	0.305*	0.002	-0.090*	0.702***	-0.013
Married	-0.001	0.137	-0.097	0.073	0.264†	-0.071
Children (Total #)	-0.014	0.047	-0.026†	-0.013	0.000	-0.017
High School	0.099*	-0.363*	0.194*	0.094†	-0.435*	0.384***
> High School	0.134**	-0.583***	0.335***	0.149**	-0.916***	0.485***
Income (Logged)	0.062**	-0.435***	0.198***	0.061*	-0.515***	0.122**
Self-Rated Health (W1)	0.536***	--	--	0.483***	--	--
Psychological Distress (W1)	--	0.397***	--	--	0.406***	--
Self-Esteem (W1)	--	--	0.429***	--	--	0.357***
Network Structure [1]						
Small	0.029	-0.231	-0.016	0.088	-0.266	-0.068
Mixed	0.008	-0.052	-0.041	0.040	-0.524*	0.018
Large	0.070	-0.211	-0.062	0.114†	-0.467†	0.059
Network Composition [2]						
Diverse	-0.018	-0.315	0.340**	-0.089	-0.442†	0.300*
Female Family	-0.019	-0.398†	0.441***	-0.078	-0.284	0.362**
Family + Spouse	0.019	-0.563*	0.530***	-0.043	-0.372	0.282*
Female Spouse	-0.111	-0.373	0.360**	-0.093	-0.574†	0.350*
Female Friends	-0.020	0.003	0.301*	-0.094	-0.369	0.238†
Male-Focused	0.121†	-0.586*	0.280*	-0.070	0.036	0.294*
Intercept	1.079	16.680	3.636	1.027	14.644	5.672
Adjusted R Square	0.387	0.277	0.256	0.288	0.287	0.215

*** $p < 0.001$ ** $p < 0.01$ * $p < 0.05$ † $p < 0.10$

Notes: [1] Reference category is "Small, Not Dense"; [2] Reference category is "Restricted".

5.2.3 Psychological Distress

The second and fifth column of Table 9 presents the unweighted parameter estimates for the OLS regression of psychological distress at Wave 2 and Wave 3 on social network typologies, while controlling for the effects of psychological distress measured at baseline. Age, education and income negatively predict increases in psychological distress between Waves 1 and 2, while being Black predicts increased levels of psychological distress. While the binary variables representing network structure are in the hypothesized direction, none are statistically significant. Regarding network composition, membership in "Family + Spouse", "Male-Focused" and, to a lesser extent, a "Female Family" networks protect against increases in psychological distress between Waves 1 and 2. In examining change between Wave 1 to Wave 3, being in a "Mixed" and, to a lesser extent, "Large" social network protect against psychological. While in the expected, negative direction, the binary variables representing network composition types do not reach statistical significance at $p < 0.05$.

5.2.4 Self-Esteem

Columns three and six in Table 9 present the unweighted parameter estimates for the OLS regressions of self-esteem at Wave 2 and Wave 3 on social network typologies, while controlling for the effects of self-esteem measured at baseline. Education and income predict increases in self-esteem over time, from Wave 1 to Wave 2. The network structure types do not significantly predict increases in self-esteem between Wave 1 and 2, but network composition types do. Compared to individuals in a "Restricted" social network, membership in a "Family + Spouse," "Female Family," "Female Spouse," “Diverse,” “Female Friends,” and “Male Focused” network types predict higher levels of self-esteem by Wave 2, in descending order of magnitude. Similar results are seen for changes between Wave 1 and Wave 3. Again, it is the network composition types that significantly predict increases in self-esteem over time. Compared to individuals in the “Restricted” network, those in other network composition types exhibit increases in self-esteem between Wave 1 and 3.

5.2.5 Person-Centered vs. Variable Centered Approach

Table 10 presents the parameter estimates for the regressions of self-rated health, psychological distress and self-esteem on network variables, after controlling for baseline health status. These network variables were the same ones used to construct the network structure and composition typologies. Similar to variable-centered analysis conducted using the cross-sectional data above, the purpose of this analysis is to compare the predictive utility of a variable-centered vs. person-centered approach.

Table 10: Regression of Self-Rated Health, Psychological Distress and Self-Esteem on Social Network Variables, ACL 1989 and 1994, Not Weighted.

	Wave 2 (N = 2,812)			Wave 3 (N = 2,360)		
	SRH	**DEP**	**SE**	**SRH**	**DEP**	**SE**
Background Factors:						
Age	-0.004***	-0.011**	0.001	-0.001	-0.006	-0.010***
Female	-0.065†	0.039	-0.132*	0.012	-0.100	-0.118†
Black	-0.019	0.269†	0.003	-0.091*	0.648***	0.025
Married	0.008	0.243	-0.078	0.070	0.294†	-0.110
Children (Total #)	-0.014†	0.043	-0.026†	-0.012	-0.001	-0.017
High School	0.101*	-0.363*	0.197*	0.095†	-0.405*	0.373***
> High School	0.140**	-0.580***	0.335***	0.151**	-0.862***	0.458***
Income (Logged)	0.062**	-0.417***	0.198***	0.061*	-0.493***	0.111*
Self-Rated Health (W1)	0.534***	--	--	0.481***		
Psychological Distress (W1)	--	0.394***	--		0.404***	
Self-Esteem (W1)	--	--	0.429***			0.355***
Network Structure						
Network Size (Help/Advise)	0.000	-0.011	-0.003	0.000	-0.066**	0.019*
Network Size (Share Feelings)	0.014	-0.005	0.005	0.007	-0.012	0.027
Network Density	0.018	-0.065	-0.017	0.024	0.026	-0.063*
Network Composition						
Spouse Nom	-0.031	-0.424*	-0.058	0.011	-0.192	0.134
Family Nom	0.027	-0.244	0.046	0.001	0.065	0.038
Friend Nom	0.005	-0.097	-0.115	-0.008	-0.106	0.015
All Female Noms	-0.081	0.009	0.414***	-0.097	-0.304	0.228
All Male Noms	0.094	-0.335	0.330*	-0.078	0.128	0.207
Mixed Gender Noms	-0.057	0.030	0.462**	-0.087	-0.260	0.130
Intercept	1.046	16.694	3.676	1.019	14.509	5.823
Adjusted R Square	0.387	0.277	0.256	0.287	0.289	0.218

*** $p < 0.001$ ** $p < 0.01$ * $p < 0.05$ † $p < 0.10$

The network variables examined here are not significant predictors of increases in self-rated health by Wave 2 or Wave 3. Regarding psychological distress, the binary variable indicating whether or not a respondent nominated a spouse/partner as a close confidant significantly protect against increased psychological distress by Wave 2. But, this variable is no longer significant in predicting increases in psychological distress by Wave 3. The size of the network providing instrumental support significantly protects against increases in psychological distress between Waves 1 and 3 (but not between Waves 1 and 2).

Regarding self-esteem, having networks composed of all women, all men, or a mixed composition significantly predicts increases in self-esteem between Waves 1 and 2 (the reference group here is those who did not nominate a close confidant or did not report the gender of the close confidants nominated). Interestingly, these variables do not predict increases in self-esteem at Wave 3. But, the size of a respondents' instrumentally supportive network and network density predict increases in self-esteem by Wave 3. Larger instrumentally supportive networks predict increases in self-esteem by Wave 3. In contrast, denser networks are associated with a lower probability of increased self-esteem by Wave 3. It is interesting that few variables representing network composition predict increases in mental health by Wave 2 (3 years after baseline), but the variables representing network size predict mental health at Wave 3 (8 years after baseline).

Comparing Tables 9 and 10, it is apparent that the person-centered approach to measuring social networks presents a more consistent picture of the effects of networks on health. We see in Table 9 that social network composition types predict increases in both psychological distress and self-esteem at Wave 2, and, to a lesser extent, at Wave 3, with all parameter estimates in the expected direction. This analysis provides another example of the utility of using typologies to measure social networks.

5.3 Conclusions

This chapter examines the relationships between the social network typologies developed in Chapter 3 and measures of physical and mental health. This chapter builds on past research in a number of ways. First, I combine a person-centered approach to measuring social networks with data on personal networks. Using respondent reports of close confidants, I classify the sample by their membership in specific network structure and composition types. Second, I examine their relationships with three health indicators representing physical health, psychological distress and positive mental health. Third, I conduct both cross-sectional and longitudinal analyses; the cross-sectional analyses examine the associations between the network typologies and health, and the longitudinal analyses determine whether network typologies can predict changes in health across time. Lastly, this person-centered approach is compared with a variable-centered approach to show its superior utility in predicting health outcomes.

In the cross-sectional analyses, there are strong associations between network structure and composition and indicators of mental health. However, the relationships between network structure and composition and physical health are weak, at best. Although all parameter estimates were in the hypothesized direction, membership in a network composed primarily of men ("Male-Focused") was the only composition type that was significantly associated with poor/fair self-rated health. As hypothesized, membership in networks characterized by having a large number of instrumentally and emotionally supportive ties are protective against depressive symptoms and also promote high levels of self-esteem. In addition, membership in a socially restricted network was associated with higher depressive symptom counts and low self-esteem. Individuals in diverse networks and those composed of a spouse and/or family members reported lower levels of depressive symptoms and were more likely to report high self-esteem.

In the analyses presented in this chapter, belonging to a social network composed primary of friends ("Female Friends") was not significantly different from belonging to a restricted network in terms of mental and physical health. Friendship and peer relationships are viewed as voluntary, while kinship relationships are viewed as involuntary, characterized by feelings of obligation and less vulnerable to dissolution over time. Much of the past research, predominantly derived from white samples, has shown that voluntary interpersonal attachments have been positively associated with life quality, while involuntary social attachments are not (Ellison 1990). Indeed, friendships are less likely to have negative effects on older adults compared with family relationships, which may trigger negative effects when social burdens and demands are too high (Crohan and Antonucci 1989). Rook (1987) found that, among a small sample of older women, reciprocity in social exchanges with friends was significantly related to relationship satisfaction, feelings of closeness and comfort, although this was not true for reciprocity in social exchanges with adult children. Among a national sample of black Americans, Ellison (1990) found that family closeness was associated with both life satisfaction and happiness, whereas friendship only significantly predicted happiness. Within a diverse social network characterized by both family members and friends, family members may meet an individual's need for practical or instrumental assistance, leaving an individual free to enjoy shared leisure time, interests and activities with their friends (Rook 1987). Individuals in networks composed entirely of friends may not have family members to provide them with practical assistance. They may need to rely on friends and/or peers for this assistance, but are aware that asymmetrical social exchanges may endanger the existence of their friendships.

Another important point to note is the role of men as close confidants in social networks. The social network type dominated by male confidants ("Male-Focused") was negatively associated with poor/fair self-rated health and depressive symptoms at baseline, as well as positively associated with reports of high self-esteem. In addition, membership in the "Male-Focused" network was protective against increases in psychological distress over three years, and predicted increases in self-esteem over the course of three and eight years. What are the potential reasons as to why networks composed of men may be consistently beneficial for mental and physical health? First, men may provide different forms of support than women. They may be more likely to provide financial assistance or certain types of instrumental assistance, while women may be more likely to provide emotional support to their close confidants. Second, in addition to providing different *types* of support, men may provide more forms of social support to their network members than women. Very few studies have examined gender differences in reports of giving and receiving of social support, resources and aid to network members. Antonucci and Akiyama (1987) find that both men and women report providing multiple types of social support – such as confiding in, reassuring, giving respect to, providing sick care, talking when upset and talking about health - to at least one member of their network. While men report that they are more likely to provide these types of support to their spouse, women report they are more likely to provide these types of support to their children and friends.

The longitudinal analyses provide *some* support for social causation, i.e., that social networks affect health. Again, the social network typologies were better predictors of mental health over time than of physical health over time. Although stability over time characterized most respondents for all three health measures, this was especially true regarding self-rated health. Thus, the low variability in self-rated health may partially explain the absence of significant relationships between self-rated health and social network types. Compared to those in “Restricted” networks, respondents who belonged to networks composed of family (“Diverse,” “Female Family,” and “Family + Spouse”) or primarily of men (“Male-Focused”) were protected against increases in psychological distress between Waves 1 and 2. In addition, membership in family-focused, friend-focused or male-focused networks predicted increases in levels of self-esteem at Waves 2 and 3.

While these analyses provide *some* support for social causation, it is possible that both social causation and selection processes are at work in producing the cross-sectional associations presented here. Therefore, the fifth chapter will use structural equation modeling to understand the dynamic and most likely reciprocal relationship between social networks and health.

6. Distinguishing Between Social Causation and Selection

Past research has provided support for the relatively robust relationships between social networks and mortality, physical health, and mental health. Much of this research purports a social causation explanation, where individuals' social environments are viewed as directly or indirectly exerting influences on well-being. Scholars have proposed that social networks, social relationships and social ties may indirectly influence well-being through a number of potential pathways, including the provision of emotional support (e.g., the sense that one is loved and cared for), instrumental support (e.g., help with tasks), and informational (e.g., advice) support, access to material resources, social influence, social control, social engagement and attachment (Umberson et al. 2010; Berkman and Glass 2000).

Another potential explanation for the robust relationships between social networks and various indicators of well-being is social selection, which refers to a process where persons' health and well-being selects them into social networks with particular attributes. Healthier individuals may be more likely to attract or maintain social relationships than their less healthy counterparts, while unhealthy individuals may even face a higher likelihood of social rejection when attempting to initiate social relationships. Recent research among older U.S. adults finds that those with better health receive more "time-spent" nominations from their peers, even after controlling for the number of nominations they send out, indicating that perhaps healthier seniors enjoy higher social status compared to their less healthy counterparts (Schafer 2011). Even among adolescents, those with poor self-rated health receive fewer friendship nominations from peers, are more likely to become social isolates, and occupy less central/ more marginal positions in the network over time compared to their healthier counterparts (Haas et al. 2010). Lastly, it may be difficult for unhealthy individuals to maintain their existing social relationships due to social withdrawal or avoidance by loved ones and peers. Social avoidance or rejection by network members may potentially arise because of the heavy burden sick individuals place on others. The effects of distress may be cumulative and more intense in close, personal relationships characterized by greater interaction. Social withdrawal and social rejection most likely are mutually reinforcing processes (Johnson 1991). Persons who are rejected by their peers may be more likely to withdraw from social interaction, and persons who do not participate in social activities may be more likely to suffer from rejection when attempting to initiate social contact. Interestingly, research conducted using data from Add Health finds that depressed adolescents have lower levels of social integration due primarily to withdrawal from social network ties over time (Schaefer et al. 2011).

Early research in psychiatry highlighted the mutually-enforcing cycle between depression and social context (Coyne 1976). James Coyne (1976) found that the social relationships of depressed persons may become fewer or more limited over time due to the mechanisms of social withdrawal or rejection, but the increasingly limited social context also contributes to ongoing depressive symptoms. Johnson (1991) used structural equation modeling among a sample of adults aged 20-64 in an effort to evaluate the separate contributions of social causation and social selection in the association between social networks and psychological distress. He found support for social selection in that psychological distress (as measured at baseline) predicted decreases in primary social relationships (i.e., social relationships with family members and close friends) one year later, although psychological distress did not predict any change in secondary social relationships (i.e., measured as group membership and church attendance). Johnson (1991) also found support for social causation, where primary social relationships (as measured at baseline) predicted lower levels of psychological distress one year later. Johnson's findings provide evidence for the dynamic, reciprocal relationship between social ties and psychological distress, although he reports to have found a greater effect for social causation than for social selection.

While many studies have examined the contribution of social causation and/or selection in the relationship between social support and health, few have examined the contribution of these processes on the relationships between *social networks* and health. This research builds on Johnson's work by using longitudinal panel data from a nationally representative study to examine the contributions of social causation vs. selection on the relationships between social network structure and three indicators of well-being (self-rated health, psychological distress and self-esteem). I simultaneously estimate the effect of social causation and. selection by using autoregressive cross-lagged models within a structural equation framework. Using this analytical method, I examine the first two waves of data, which are three years apart. This is a longer time frame than that analyzed by Johnson (1991), and may allow for more change in physical health, mental health or social network structure over time.

6.1 Structural Equation Modeling

Structural equation modeling (SEM), also known as covariance structural analysis, is a useful approach for this research question for several reasons. First, structural equation models can simultaneously estimate regression equations where variables are treated as both *predictors* (independent variables) and *predicted* (dependent variables), assessing reciprocal relationships within the same analysis (Johnson 1991; Bowen and Guo 2012). Second, this method can simultaneously perform factor analysis and compute regression equations, accommodating regression relationships among different latent variables or among latent and observed variables (Bowen and Guo 2012).

The autoregressive cross-lagged model assumes that the current value of a variable is determined by the previous value of that variable (Bollen and Zimmer 2010). In this analysis, I regress a Time 2 dependent variable on its Time 1 (baseline) measure. Autoregressive cross-lagged models are similar to residual change score models using OLS regression in that they assess the degree to which baseline (Time 1) independent variables predict a subsequent (Time 2) dependent variable, while controlling for the effects of the dependent variable at baseline (Time 1). But, autoregressive models within an SEM framework have several advantages over the residual change score modeling, including the ability to incorporate multiple indicators into the measurement of a latent variable, the ability to estimate relationships between observed variables and latent factors, and the ability to simultaneously assessing reciprocal effects within a single model.

Figure 4 is a path diagram of the analyses presented in this chapter, using self-esteem as the dependent variable. This path diagram presents both the measurement and structural components for the autoregressive cross-lagged model used in this chapter. As portrayed in Figure 4, there are two latent factors (network structure and self-esteem) measured at two points in time. Each latent factor is measured using three indicator (observed) variables. The analyses presented here will simultaneously test the following relationships while controlling for the effects of a number of social, demographic and network factors: (1) the effect of network structure at Time 1 on network structure at Time 2; (2) the effect of self-esteem at Time 1 on self-esteem at Time 2; (3) the effect of network structure at Time 1 on self-esteem at Time 2; and (4) the effect of self-esteem at Time 1 on network structure at Time 2. The coefficients from these last two models (as exemplified by pathways Υ_{41} and Υ_{32} in Figure 4) will directly test the magnitudes and statistical significance of social causation and social selection processes. The analyses performed for psychological distress and self-rated health are similar to those represented in Figure 4, with a few exceptions. Similar to self-esteem, psychological distress is also measured as a latent factor, but is derived from eleven indicator (observed) variables. Unlike self-esteem and psychological distress, self-rated health is not measured as a latent factor, but simply as an observed variable. The interpretation of results from the autoregressive cross-lagged model is similar to interpretation of results using residual change scores in OLS regression.

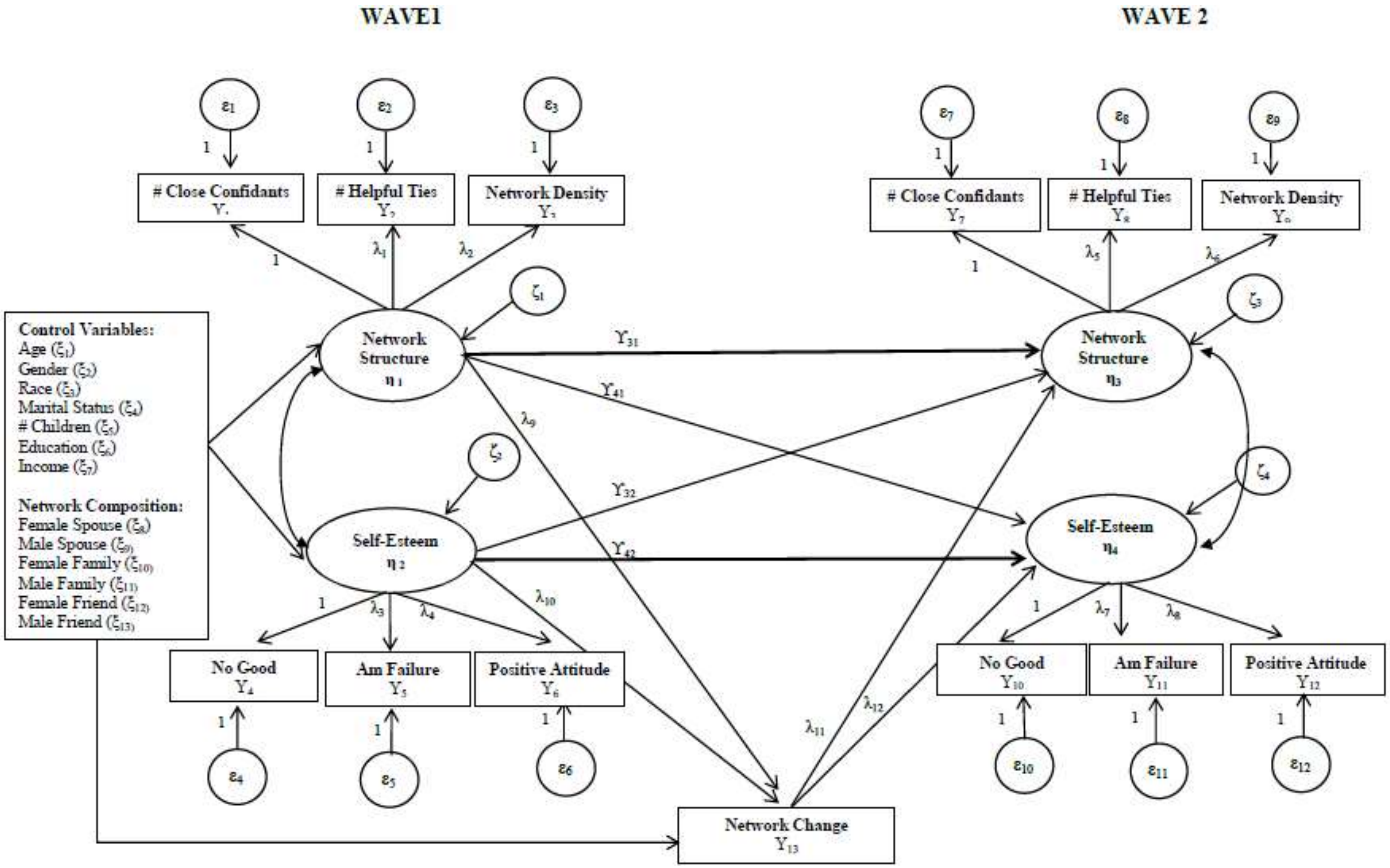

Figure 4: Path Diagram for Structural Equation Modeling of Self-Esteem, ACL 1986-1989.

6.2 Hypotheses

The social causation hypothesis predicts that social context has direct and/or indirect influences on well-being. Here, well-being is measured by the observed variable, self-rated health, and two latent factors, psychological distress and self-esteem. Referred to in this chapter as the social causation hypothesis, I predict that social network structure at Time 1 will have a positive effect on self-rated health and self-esteem at Time 2. I also hypothesize that social network structure at Time 1 will have a negative effect on psychological distress at Time 2.

The social selection hypothesis predicts that well-being influences individuals' social relationships, social ties and social network attributes. Referred to as the social selection hypothesis in this chapter, I hypothesize that self-rated health and self-esteem at Time 1 will have a positive influence on social network structure at Time 2. I also hypothesize that psychological distress at Time 1 will have a negative influence on social network structure at Time 2.

As portrayed in Figure 4, network structure is a latent factor measured using three observed variables (number of instrumentally helpful ties, number of close confidants and network density). Previous findings in Chapter 2 showed that *both* network structure and composition had separate, distinct influences on mental health (and physical health, to a lesser extent). Unfortunately, the Americans' Changing Lives survey only collects relationship type and gender information on respondents' three closest confidant during the first wave (1986). The second wave (1989) is more limited in terms of social network data, but does contain information on the relationship type and gender of each respondent's primary close confidant. Thus, while I cannot ascertain changes in network composition between the two waves, I can roughly measure whether a respondent's primary close confidant has changed across waves. In the forthcoming analyses, I have included a set of binary variables measuring the gender and relationship type of respondents' closest confidant at Time 1 ("Female spouse," "Male spouse," "Female family member," "Male family member," "Female friend," and "Male friend"), with individuals who did not nominate a close confidant used as the reference category. These binary variables are regressed on Time 1 measures of network structure, health and a variable labeled "network change". Network change is a binary variable roughly measuring whether or not a respondent's closest confidant changed between Time 1 and Time 2[1]. According to Kahn and Antonucci (1980) in their social convoy model, close, intimate relationships are stable over time and not likely to change due to changes in social roles, geographic proximity or social contact. Network change in a close confidant may arise due to a number of potential life circumstances, including marital dissolution, relocation, retirement, sickness or death, or through processes such as social withdrawal, avoidance or rejection. In accordance with social causation, I hypothesize that network change will have a negative effect on self-rated health and self-esteem, but a positive effect on psychological distress at Time 2. In accordance with the social selection, I hypothesize that high levels of self-rated health and self-esteem will protect against

[1] If the gender and relationship type of the primary close confidant changed between Time 1 and 2, then the respondent was coded as having experienced network change. In addition, if the respondent reported having a close confidant at Time 1, but then reported no close confidant at Time 2, he/she was coded as experiencing network change. Lastly, if the respondent reported having no close confidant at Time 1, but then reported a close confidant at Time 2, he/she was coded as experiencing network change. This is a rough measure of network change and I was not able to ascertain if a close confidant was the same person for respondents who reported the same gender and relationship type for their primary close confidant over time.

network change, but psychological distress will increase the likelihood of network change between Time 1 and Time 2.

6.3 Self-Rated Health

Several models were tested in order to assess the contributions of social causation and social selection to the overall model fit. Table 11 presents summary information comparing four separate models. Model 1 is considered the null model and provides a baseline against which the other three models may be compared. Model 1 estimates the stability coefficients for the latent factor, network structure, and the observed variable, self-rated health. It does this by estimating the effect of the baseline (T1) value on its T2 value. This model does not estimate paths between network structure and self-rated health over time or between network change in primary close confidant and self-rated health over time. Model 2 provides a test of the social causation hypotheses and estimates a path between network structure at Time 1 and self-rated health at Time 2; in addition, Model 2 estimates a path between network change (between Time 1 and 2) and self-rated health at Time 2. Model 3 provides a test of the social selection hypotheses and estimates a path between self-rated health at Time 1 and network structure at Time 2; Model 3 also estimates a path between self-rated health at Time 1 and network change (occurring between Time 1 and 2). Model 4 is the final model, and incorporates tests of both the social causation and selection hypotheses. Model 4 estimates paths between network structure at T1 and self-rated health at T2, as well as self-rated health at T1 and network structure at T2. In addition, Model 4 estimates paths between network change (occurring between Time 1 and 2) and self-rated health at Time 2, and between self-rated health at

Time 1 and network change. Models 2 – 4 are all nested within Model 1, which is the baseline model used for comparison. As portrayed in Table 11, Model 4 produces a difference in Chi-Square equal to 29.914, which is superior to the change in Chi-Square produced by either Model 2 or 3 (degrees of freedom = 4, $p < 0.001$). Thus, Model 4 will be the accepted model and the one discussed below.

Table 11: Chi-Square Associated with a Null Model and Models of Social Causation and Selection for Self-Rated Health, ACL 1986-1989.

Model	Chi-Square	Degrees of Freedom	Chi-Square Difference
Null Model	1417.954	102	--
Social Causation	1412.238	100	5.716
Social Selection	1396.475	100	21.479***
Full	1391.04	98	26.914***

*** p < 0.001 ** p < 0.01 * p < 0.05 † p < 0.10

The model Chi-Square is 1391.04 with 98 degrees of freedom. A nonsignificant p-value associated with χ^2 implies that the input and implied matrices are statistically equivalent, but it is difficult to meet the criterion for nonsignificance with a large sample size (Bowen and Guo 2012). Therefore, there are several goodness-of-fit measures available to evaluate the fit of structural equation models. The Root Mean Square Error of Approximation (RMSEA) is a measure of how close the implied matrix is to the observed matrix, and takes into account the complexity of the model, rewarding simpler, more parsimonious models. A value of 0.05 indicates close fit and a value between 0.05 and 0.08 indicates reasonable fit (Bowen and Guo 2012). The RMSEA for this model is 0.068, with a 90% confidence interval of 0.65 – 0.71, indicating reasonable fit. The Standardized Root Mean Square Residual (SRMR) is 0.045, with values below 0.05 indicating good fit of the model to the data. The Comparative Fit Index (CFI) and

Tucker-Lewis Index (TLI) are additional goodness-of-fit indices, where values of 0.95 or higher indicate a good fit. For this model, the CFI and TLI are 0.772 and 0.643, respectively, which are lower than desirable.

Table 12 presents the factor loadings of the observed variables on the latent factor network structure for the measurement portion of the model. The number of close confidants appears to be the strongest indicator of network structure at Time 1 and Time 2, while the factor loadings for network density are much weaker. The R-Square statistic tells how much variance of a dependent variable is explained by the model. For Time 1 measures, the R-Square is highest for the observed variable measuring number of close confidants ($R^2 = 0.589$), followed by number of instrumentally helpful ties ($R^2 = 0.248$), and network density ($R^2 = 0.049$). The same is true for Time 2 measures. Thus, the latent factor, network structure, explains little of the variation in the observed variable measuring network density.

Table 13 presents structural parameter estimates for the full model. Support for social causation is seen in the second-to-last column of Table 13, where the effect of network structure (at Time 1) on self-rated (at Time 2) is statistically significant and positive ($\beta = 0.033$, $p < 0.05$). Having a larger, denser network structure is predictive of increasing self-rated health over time. Support for social selection is seen in the last column of Table 13, where the effect of self-rated health (at Time 1) on network structure (at Time 2) is also statistically significant and positive ($\beta = 0.126$, $p < 0.001$). Having better self-rated health at Time 1 is predictive of having a larger, denser social network structure over time. Interestingly, there were no statistically significant correlations between network structure and self-rated health within the same time periods. The correlation between network structure and self-rated health at Time 1 was r = 0.004 and at Time 2 was r = 0.045. Self-rated health at Time 1 does not significantly predict network change, and network change does not have a significant effect on self-rated health at Time 2.

Table 12: Factor Loadings of Observed Indicators of Network Structure, Measurement Model, ACL 1986 - 1989.

		Wave 1				Wave 2			
Latent Factors	Observed Indicators	Path	S.E.	Standardized Coefficient	R-Square	Path	S.E.	Standardized Coefficient	R-Square
Network Structure									
	# Close Confidants	1.000	0.000	0.767	0.589	1.000	0.000	0.634	0.402
	# Helpful Ties (Logged)	0.296	0.020	0.498	0.248	0.361	0.022	0.585	0.343
	Network Density	0.217	0.023	0.221	0.049	0.179	0.023	0.188	0.035

Table 13: Structural Parameter Estimates for Social Causation and Selection Models for Self-Rated Health, ACL 1986-1989.

		Independent Variables								
		Age	Female	Black	Married	Children (#)	Education	Income (Logged)	Female Spouse	Male Spouse
Dependent Variables										
Network Structure - T1	(a)	0.003†	-0.190*	-0.272***	0.053	0.031*	0.032**	0.070†	2.029***	2.275***
	(b)	0.002	0.077	0.064	0.070	0.014	0.010	0.038	0.133	0.147
	(c)	0.039	-0.139	-0.199	0.038	0.047	0.080	0.051	1.484	1.664
Self-Rated Health - T1	(a)	-0.012***	0.009	-0.093*	- 0.155***	-0.011	0.040***	0.249***	0.213**	0.141†
	(b)	0.001	0.053	0.044	0.048	0.010	0.007	0.026	0.079	0.082
	(c)	-0.186	0.008	-0.084	-0.140	-0.021	0.123	0.226	0.192	0.128
Network Change	(a)	-0.002*	-0.004	0.043*	0.018	0.008†	-0.007†	-0.031*	-0.305***	-0.219***
	(b)	0.001	0.026	0.022	0.023	0.003	0.003	0.013	0.044	0.047
	(c)	-0.053	-0.008	0.086	0.036	0.034	-0.045	-0.061	-0.612	-0.439
Network Structure - T2	(a)	--	--	--	--	--	--	--	--	--
	(b)	--	--	--	--	--	--	--	--	--
	(c)	--	--	--	--	--	--	--	--	--
Self-Rated Health - T2	(a)	--	--	--	--	--	--	--	--	--
	(b)	--	--	--	--	--	--	--	--	--
	(c)	--	--	--	--	--	--	--	--	--

*** $p < 0.001$ ** $p < 0.01$ * $p < 0.05$ † $p < 0.10$

Notes: (a) Unstandardized Coefficient; (b) Standard Error; (c) Standardized Coefficient

Table 13 (Cont'd): Structural Parameter Estimates for Social Causation and Selection Models for Self-Rated Health, ACL 1986-1989.

		Independent Variables							R-Square
		Female Family	Male Family	Female Friend	Male Friend	Network Change	Network Structure - T1	Self-Rated Health - T1	
Dependent Variables									
Network Structure - T1	(a)	2.302***	2.392***	2.047***	2.194***	--	--	--	0.348
	(b)	0.129	0.159	0.126	0.142	--	--	--	
	(c)	1.683	1.749	1.497	1.604	--	--	--	
Self-Rated Health - T1	(a)	0.192**	0.210*	0.073	0.217**	--	--	--	0.178
	(b)	0.066	0.091	0.068	0.079	--	--	--	
	(c)	0.174	0.190	0.066	0.196	--	--	--	
Network Change	(a)	-0.203***	-0.022	-0.137***	0.008	--	0.003	0.003	0.063
	(b)	0.041	0.051	0.040	0.045	--	0.011	0.009	
	(c)	-0.408	-0.045	-0.274	0.015	--	0.008	0.008	
Network Structure - T2	(a)	--	--	--	--	-0.007	0.612***	0.126***	0.472
	(b)	--	--	--	--	0.060	0.040	0.027	
	(c)	--	--	--	--	-0.003	0.668	0.111	
Self-Rated Health - T2	(a)	--	--	--	--	-0.007	0.033*	0.594***	0.37
	(b)	--	--	--	--	0.033	0.014	0.015	
	(c)	--	--	--	--	-0.003	0.041	0.603	

*** $p < 0.001$ ** $p < 0.01$ * $p < 0.05$ † $p < 0.10$

Notes: (a) Unstandardized Coefficient; (b) Standard Error; (c) Standardized Coefficient

Table 13 also portrays the parameter estimates for the binary variables representing the gender/relationship type of the closest confidant. As shown in row 2 of Table 13, individuals who report their closest confidant was a female spouse/partner, female family member, male family member or male friend had significantly higher levels of self-rated health at Time 1 than those who reported no close confidants. Individuals whose close confidant was reported to be a male spouse/partner or female friend did not differ significantly in terms of self-rated health at Time 1 than those who reported having no close confidants. Lastly, row 3 of Table 13 shows the effect of gender/relationship type of closest confidant on network change. Individuals nominating a female spouse/partner, male spouse/partner, female family member or female friend are least likely to change their closest confidant between Time 1 and 2. But, those nominating a male family member or male friend are just as likely to undergo network change as those who did not nominate a close confidant at Time 1.

6.4 Psychological Distress

Table 14 presents summary information comparing four separate models – the null, social causation, social selection and the full model. As portrayed in Table 14, Model 4 produces a difference in Chi-Square equal to 31.569, which is superior to the change in Chi-Square produced by either Model 2 or 3 (degrees of freedom = 4, $p < 0.001$). Thus, Model 4 will be the accepted model and the one discussed below.

Table 14: Chi-Square Associated with a Null Model and Models of Social Causation and Selection for Psychological Distress, ACL 1986-1989.

Model	Chi-Square	Degrees of Freedom	Chi-Square Difference
Null Model	6198.437	710	--
Social Causation	6180.297	708	18.14***
Social Selection	6184.311	708	14.126***
Full	6166.868	706	31.569***

*** $p < 0.001$ ** $p < 0.01$ * $p < 0.05$ † $p < 0.10$

The Chi-Square for the model is 6166.868 with 706 degrees of freedom. The CFI and TLI are 0.762 and 0.736, respectively, which is lower than desirable. But, the RMSEA is 0.052, with a 90% confidence interval from 0.051 to 0.053, and the SRMR is 0.045, both indicating that the model fits the data reasonably well.

Table 15 presents the factor loadings of the observed variables on the latent factors, psychological distress and network structure, for the measurement portion of the model. The factor loadings for the latent factor network structure are almost identical to the factor loadings presented in Table 12. The strongest indicators of the latent factor psychological distress are variables indicating the extent to which respondents reported being sad, depressed or lonely. The latent factor psychological distress explains the greatest amount of variance for these three observed variables at Time 1 and Time 2.

Table 16 presents structural parameter estimates for the full model. Support for social causation is seen in the second-to-last column of Table 16, where the effect of network structure (at Time 1) on psychological distress (at Time 2) is statistically significant and negative ($\beta = -0.021$, $p < 0.01$). Thus, a larger, denser network structure is predictive of decreases in levels of psychological distress over time. The third to last column of Table 16 also provides support for social causation. The parameter estimate for the effect of network change on psychological distress at Time 2 is positive and statistically significant ($\beta = 0.046$, $p < 0.01$), indicating that a change in closest confidant between Time 1 and 2 predicts higher psychological distress by Time 2. Support for social selection is seen in the last column of Table 16, where the effect of psychological distress (at Time 1) on network structure (at Time 2) is also statistically significant and negative ($\beta = -0.292$, $p < 0.001$). Thus, having higher levels of psychological distress at baseline is predictive of having smaller, less dense network structure over time. There are also statistically significant, albeit small correlations between network structure and psychological distress as measured at Time 1 ($r = -0.068$) and Time 2 ($r = -0.066$).

Table 15: Factor Loadings of Observed Indicators of Psychological Distress and Network Structure, Measurement Model, ACL 1986 - 1989.

		Wave 1				**Wave 2**			
Latent Factors	Observed Indicators	Path	S.E.	Standardized Coefficient	R-Square	Path	S.E.	Standardized Coefficient	R-Square
Psychological Distress									
	Depressed	1.000	0.000	0.725	0.525	1.000	0.000	0.744	0.554
	Effort	0.832	0.032	0.519	0.269	0.803	0.031	0.517	0.267
	Restless Sleep	0.754	0.032	0.471	0.222	0.731	0.031	0.473	0.224
	Lonely	0.913	0.027	0.673	0.453	0.905	0.029	0.634	0.402
	Unfriendly	0.497	0.023	0.431	0.185	0.430	0.024	0.372	0.138
	Appetite	0.613	0.027	0.463	0.214	0.584	0.027	0.441	0.195
	Sad	1.004	0.027	0.745	0.556	0.994	0.027	0.724	0.524
	Dislike	0.498	0.021	0.478	0.229	0.475	0.021	0.466	0.217
	Get Going	0.721	0.028	0.521	0.271	0.762	0.028	0.548	0.301
	Happy	0.787	0.028	0.564	0.318	0.762	0.029	0.526	0.277
	Enjoy Life	0.669	0.027	0.503	0.253	0.628	0.027	0.464	0.215
Network Structure									
	# Close Confidants	1.000	0.000	0.749	0.561	1.000	0.000	0.615	0.378
	# Instrumentally Helpful Ties (Logged)	0.314	0.022	0.516	0.266	0.381	0.022	0.600	0.360
	Network Density	0.225	0.024	0.224	0.050	0.195	0.024	0.198	0.039

Table 16: Structural Parameter Estimates for Social Causation and Selection Models for Psychological Distress, ACL 1986-1989.

		Independent Variables								
		Age	Female	Black	Married	Children (#)	Education	Income (Logged)	Female Spouse	Male Spouse
Dependent Variables										
Network Structure - T1	(a)	0.002	-0.182*	-0.277***	0.048	0.031*	0.031**	0.075*	1.969***	2.199***
	(b)	0.002	0.076	0.064	0.069	0.014	0.010	0.037	0.138	0.154
	(c)	0.029	-0.137	-0.207	0.036	0.048	0.080	0.057	1.475	1.647
Psychological Distress - T1	(a)	-0.005***	0.046†	0.044*	-0.081***	0.002	-0.015***	-0.078***	-0.154***	-0.108**
	(b)	0.001	0.024	0.020	0.022	0.004	0.003	0.012	0.035	0.037
	(c)	-0.197	0.103	0.100	-0.182	0.009	-0.115	-0.177	-0.348	-0.243
Network Change	(a)	-0.002**	-0.004	0.043*	0.017	0.008†	-0.007†	-0.030*	-0.303***	-0.217***
	(b)	0.001	0.026	0.022	0.023	0.023	0.003	0.013	0.044	0.047
	(c)	-0.054	-0.008	0.086	0.035	0.034	-0.045	-0.060	-0.608	-0.435
Network Structure - T2	(a)	--	--	--	--	--	--	--	--	--
	(b)	--	--	--	--	--	--	--	--	--
	(c)	--	--	--	--	--	--	--	--	--
Psychological Distress - T2	(a)	--	--	--	--	--	--	--	--	--
	(b)	--	--	--	--	--	--	--	--	--
	(c)	--	--	--	--	--	--	--	--	--

*** $p < 0.001$ ** $p < 0.01$ * $p < 0.05$ † $p < 0.10$

Notes: (a) Unstandardized Coefficient; (b) Standard Error; (c) Standardized Coefficient

Table 16 (Cont'd): Structural Parameter Estimates for Social Causation and Selection Models for Psychological Distress, ACL 1986-1989.

		Independent Variables							R-Square
		Female Family	Male Family	Female Friend	Male Friend	Network Change	Network Structure - T1	Psychological Distress - T1	
Dependent Variables									
Network Structure - T1	(a)	2.232***	2.310***	1.981***	2.123***	--	--	--	0.346
	(b)	0.137	0.166	0.132	0.148	--	--	--	
	(c)	1.672	1.730	1.484	1.590	--	--	--	
Psychological Distress - T1	(a)	-0.084**	-0.131***	-0.030	-0.109**	--	--	--	0.141
	(b)	0.030	0.041	0.030	0.036	--	--	--	
	(c)	-0.189	-0.295	-0.069	-0.245	--	--	--	
Network Change	(a)	-0.201***	-0.020	-0.135***	0.010	--	0.002	-0.003	0.063
	(b)	0.041	0.051	0.040	0.045	--	0.012	0.025	
	(c)	-0.404	-0.040	-0.271	0.020	--	0.006	-0.002	
Network Structure - T2	(a)	--	--	--	--	0.002	0.611***	-0.292***	0.494
	(b)	--	--	--	--	0.058	0.045	0.079	
	(c)	--	--	--	--	0.001	0.671	-0.107	
Psychological Distress - T2	(a)	--	--	--	--	0.046**	-0.021**	0.564***	0.347
	(b)	--	--	--	--	0.016	0.008	0.024	
	(c)	--	--	--	--	0.052	-0.062	0.566	

*** $p < 0.001$ ** $p < 0.01$ * $p < 0.05$ † $p < 0.10$

Notes: (a) Unstandardized Coefficient; (b) Standard Error; (c) Standardized Coefficient

Social network composition, as measured by the gender and relationship type of the respondents' closest confidant, also has significant effects on network structure (T1), psychological distress (T1) and network change. Row 2 of Table 16 shows that all binary variables representing gender and relationship type of closest confidant are statistically significant and negative, except for the variable, "Female friend". Thus, individuals who report that their closest confidant is a female friend do not have significantly lower levels of psychological distress at Time 1 compared to those who report having no one to confide in. The effect of gender/relationship type of closest confidant on network change is similar to the results presented above.

6.5 Self-Esteem

Table 17 presents summary information comparing four separate models – the null, social causation, social selection and the full model. As portrayed in Table 17, Model 4 produces a difference in Chi-Square equal to 11.978. While not large, this Chi-Square difference is superior to the change in Chi-Square produced by either Model 2 or 3 (degrees of freedom = 4, $p < 0.05$). Thus, Model 4 will be the accepted model and the one discussed below.

Table 17: Chi-Square Associated with a Null Model and Models of Social Causation and Selection for Self-Esteem, ACL 1986-1989.

Model	Chi-Square	Degrees of Freedom	Chi-Square Difference
Null Model	1818.236	190	--
Social Causation	1811.559	188	6.677*
Social Selection	1812.41	188	5.826
Full	1806.258	186	11.978*

*** p < 0.001 ** p < 0.01 * p < 0.05 † p < 0.10

The Chi-Square value for the full model is 1806.258 with 186 degrees of freedom. The CFI and TLI are 0.773 and 0.698, respectively, which again are lower than desirable. But, the RMSEA is 0.55, with a 90% confidence interval from 0.053 – 0.057, and the SRMR is 0.042, both indicating that the model fits the data reasonably well.

Table 18 presents the factor loadings of the observed variables on the latent factors, self-esteem and network structure, for the measurement portion of the model. Again, the factor loadings for the latent factor network structure are equivalent to the factor loadings presented in Table 12 and 15. The latent factor self-esteem was derived using three indicator (observed) variables – one was positively worded and two were negatively worded. The two negatively worded variables – feeling no good or feeling like a failure – had the strongest factor loadings for the latent factor self-esteem, while the positively worded item – having a positive attitude, had a factor loading slightly above 0.4. The amount of variance explained by the latent factor self-esteem is greater for the two negatively worded items than for the positively worded item.

Table 19 presents the structural parameter estimates for the full model. There is a lack of support for social causation. There is a weak, positive effect of network structure (T1) on self-esteem (T2) ($\beta = 0.024$, $p < 0.10$), and also a weak, negative effect of network change on self-esteem (T2) ($\beta = -0.051$, $p < 0.10$). The second to last column of Table 19 provides some support for social selection. Self-esteem (at Time 1) positively influences network structure (at Time 2) ($\beta = 0.126$, $p < 0.05$). But, there is no effect of self-esteem (T1) on network change between Time 1 and 2. There is a statistically significant correlation between network structure and self-esteem at Time 1 ($r = 0.115$), but not at Time 2 ($r = 0.037$).

Table 18: Factor Loadings of Observed Indicators for Self-Esteem and Network Structure, Measurement Model, ACL 1986 - 1989.

		Wave 1				**Wave 2**			
Latent Factors	Observed Indicators	Path	S.E.	Standardized Coefficient	R-Square	Path	S.E.	Standardized Coefficient	R-Square
Self-Esteem									
	No Good	1.000	0.000	0.690	0.476	1.000	0.000	0.708	0.502
	Failure	0.825	0.036	0.674	0.455	0.852	0.036	0.698	0.487
	Positive Attitude	0.419	0.026	0.382	0.146	0.460	0.026	0.440	0.194
Network Structure									
	# Close Confidants	1.000	0.000	0.761	0.580	1.000	0.000	0.633	0.400
	# Helpful Ties (Logged)	0.301	0.020	0.503	0.253	0.361	0.022	0.584	0.341
	Network Density	0.218	0.023	0.221	0.049	0.187	0.023	0.196	0.038

Table 19: Structural Parameter Estimates for Social Causation and Selection Models for Self-Esteem, ACL 1986-1989.

		Independent Variables								
		Age	Female	Black	Married	Children (#)	Education	Income (Logged)	Female Spouse	Male Spouse
Dependent Variables										
Network Structure - T1	(a)	0.003	-0.187*	-0.281***	0.052	0.031*	0.032**	0.074*	2.015***	2.254***
	(b)	0.002	0.077	0.064	0.069	0.014	0.010	0.037	0.133	0.147
	(c)	0.032	-0.138	-0.207	0.038	0.047	0.080	0.054	1.485	1.662
Self-Esteem - T1	(a)	0.006***	-0.044	0.090*	-0.077*	0.001	0.035***	0.170***	0.261***	0.238***
	(b)	0.001	0.042	0.036	0.039	0.008	0.006	0.021	0.064	0.066
	(c)	0.147	-0.063	0.130	-0.111	0.003	0.171	0.246	0.374	0.342
Network Change	(a)	-0.002*	-0.004	0.044*	0.017	0.008†	-0.006†	-0.028*	-0.304***	-0.218***
	(b)	0.001	0.026	0.022	0.023	0.005	0.003	0.013	0.044	0.047
	(c)	-0.052	-0.009	0.088	0.034	0.033	-0.043	-0.057	-0.610	-0.438
Network Structure - T2	(a)	--	--	--	--	--	--	--	--	--
	(b)	--	--	--	--	--	--	--	--	--
	(c)	--	--	--	--	--	--	--	--	--
Self-Esteem - T2	(a)	--	--	--	--	--	--	--	--	--
	(b)	--	--	--	--	--	--	--	--	--
	(c)	--	--	--	--	--	--	--	--	--

*** $p < 0.001$ ** $p < 0.01$ * $p < 0.05$ † $p < 0.10$

Notes: (a) Unstandardized Coefficient; (b) Standard Error; (c) Standardized Coefficient

Table 19 (Cont'd): Structural Parameter Estimates for Social Causation and Selection Models for Self-Esteem, ACL 1986-1989.

		Independent Variables							**R-Square**
		Female Family	Male Family	Female Friend	Male Friend	Network Change	Network Structure - T1	Self-Esteem - T1	
Dependent Variables									
Network Structure - T1	(a)	2.288***	2.369***	2.028***	2.177***	--	--	--	0.35
	(b)	0.129	0.160	0.126	0.142	--	--	--	
	(c)	1.686	1.746	1.495	1.604	--	--	--	
Self-Esteem - T1	(a)	0.163**	0.223**	0.156**	0.224***	--	--	--	0.122
	(b)	0.054	0.073	0.055	0.064	--	--	--	
	(c)	0.235	0.321	0.224	0.321	--	--	--	
Network Change	(a)	-0.204***	-0.022	-0.137***	0.008	--	0.004	-0.009	0.063
	(b)	0.041	0.051	0.040	0.045	--	0.012	0.018	
	(c)	-0.408	-0.044	-0.275	0.016	--	0.011	-0.012	
Network Structure - T2	(a)	--	--	--	--	-0.006	0.617***	0.126*	0.474
	(b)	--	--	--	--	0.060	0.126	0.056	
	(c)	--	--	--	--	-0.002	0.669	0.070	
Self-Esteem - T2	(a)	--	--	--	--	-0.051†	0.024†	0.622***	0.398
	(b)	--	--	--	--	0.030	0.014	0.035	
	(c)	--	--	--	--	-0.036	0.046	0.615	

*** $p < 0.001$ ** $p < 0.01$ * $p < 0.05$ † $p < 0.10$

Notes: (a) Unstandardized Coefficient; (b) Standard Error; (c) Standardized Coefficient

The parameter estimates for the binary indicators of network composition are all statistically significant and positive, indicating that those who report having a close confidant have larger, denser network structure and higher self-esteem at baseline. Similar to the results reported above for self-rated health and self-esteem, individuals who nominated a male family member or male friend were more likely to undergo a change in close confidant between Time 1 and 2, compared with those who nominated a female spouse, male spouse, female family member or female friend.

6.6 Conclusions

The connection between social networks and well-being has been well-documented in the sociological, gerontology and epidemiological literatures. Interestingly, much of the research on social networks and well-being has been performed using data collected at one point in time, where the researchers' propose either a social causation or selection mechanism to aid in interpretation of results. Few studies have used data collected at two or more points in time, and even fewer have simultaneously tested hypotheses based on both social causation and selection mechanisms. This chapter builds on the work of Johnson (1991) by using autoregressive cross-lagged models within a structural equation framework to test social causation and selection hypotheses using data from a nationally representative longitudinal sample. These analyses further existing research by examining three separate indicators of well-being as dependent variables: self-rated health, psychological distress and self-esteem. I find strong support for both social causation and selection processes in examining self-rated health and psychological distress. In contrast, I only find weak support for social selection in examining self-esteem.

This study was limited in that, due to data limitations, only social network structure was measured consistently across the two time points. Social network composition was examined, but data limitations did not allow for a direct comparison between social network composition at Time 1 and Time 2. An indicator of network change in closest confidant was included in the analyses, and as hypothesized, negative predicted self-esteem (T2) and positively predicted psychological distress (T2). Unfortunately, this indictor measured whether a respondents' closest confidant changed over time, not whether the composition of the social network changed over time. More information on additional close confidants in the second wave of data would be required in order to determine this.

Despite data limitations, the results of this study demonstrate the benefits of using autoregressive cross-lagged models and provide strong support for the reciprocal, dynamic relationships between social networks and well-being over time.

7. Conclusion

Building on a strong foundation of research on the importance of social support and relationships for physical and mental health, this dissertation uses social network analysis to examine how social network structure and composition influence multiple indicators of well-being. In bridging the social network and health literatures, the most important feature of this dissertation is the use of respondents' reports of their closest confidants in measuring characteristics of the social network. Measuring social networks in this way, as opposed to simply counting the number of kinship relationships, was performed to gain a more nuanced understanding of the roles a circle of close confidants have on physical and mental health.

This research improves on past research in a number of ways. First, I used data on respondent reports of close confidants to construct social network typologies representing network structure and composition. Using personal network data provided superior information for measuring social networks than variables that have previously been used, such as those representing the presence or absence of certain social relationships (such as marital status or parental status), the perceived frequency or quality of these social relationships, and social integration (such as church attendance or group membership). Moreover, the use of personal network data allowed for the separate evaluation of network structure and composition to well-being.

Second, I used hierarchical cluster analysis to create social network typologies. Social network typologies reflect the complex, multidimensional, and aggregate nature of social life (Fiori et al. 2006). This approach is compelling because social networks are more than the sum of their parts and contain emergent properties not explained by, or even represented in, their constituent parts (Blau 1977; Auslander and Litwin 1990; Smith and Christakis 2008). In assessing the benefit of this approach, I compared the predictive utility of the person-centered approach to that of a variable-centered approach. This is the first comparison made between person-centered and variable-centered approaches of which the author is aware and the results provide some support for the superior predictive power of a person-centered approach in measuring social networks.

Although not using personal network data, a slew of past research constructed network typologies using qualitative (Wenger 1997) and quantitative methods (Cheng et al. 2009; Fiori et al. 2008; Fiori et al. 2006; Fiori et al. 2007; Litwin and Landau 2000; Litwin 1998; Litwin 1997; Litwin 2001; Litwin and Shiovitz-Ezra 2006). This dissertation extends past network typology research by constructing separate typologies for both network structure and composition. Consistent with past research, I found similar network composition types that can be classified as diverse, family-oriented, friend-oriented and restricted. In this study, a number of family-oriented compositional types, including the "Female Family," "Family + Spouse," and "Female Spouse" types, were observed. In addition, a new form of network composition, labeled "Male-focused" was found. Individuals in this group reported that all of their close confidants were men, with those close confidants representing a variety of relationship types. This group was relatively rare. A majority of the sample reported belong to networks which were composed of entirely women or of both women and men. The network structure types integrated information on the size and density of the network. Four network structure types were observed: "Large," "Mixed," "Small, Dense" and "Small, Not Dense."

The network typologies showed strong cross-sectional associations with indicators of mental health, including psychological distress and self-esteem. They were not strongly associated, however, with self-rated health. The “Large” and “Mixed” network structure types predicted fewer depressive symptom counts and higher self-esteem than the “Small, Not Dense” type. Belonging to a “Small, Dense” type was not significantly different from belonging to a “Small, Not Dense” type in regards to the health indicators examined here. Thus, network size may have a stronger influence on well-being than network density. In contrast, the network structure types were not significantly associated with reports of poor/fair self-rated health. A dichotomous self-rated health variable was used because the original distribution of responses was highly skewed. It is possible that simplifying the data in this way contributed to the finding of no effect of network structure on self-rated health.

Compared to those with a “Restricted” network composition, individuals in “Diverse,” “Female Family,” “Family Spouse,” “Female Spouse” and “Male-Focused” networks reported fewer depressive symptoms. Those in a “Diverse,” “Family Spouse,” and “Female Spouse” network also reported higher levels of self-esteem than those in the “Restricted” group.

Interestingly, individuals whose network consisted of mostly female friends were not significantly different in terms of mental health than individuals in restricted networks (or those who report having no close confidants). This finding is contrary to research on older adults that finds friendship beneficial, above and beyond that of familial ties, quite possibly because of the voluntary nature of the social relationship. Older adults derive high levels of enjoyment and satisfaction from their friends and friends can be sources of companionship as well as close confidants (Adams and Blieszner 1995). In previous studies of social network types, while the “Diverse” network type conferred the greatest health benefit, network types composed of friends were not far off, conferring rewards in terms of higher morale, lower psychological distress and better physical health (Litwin 2001; Fiori et al. 2006; Litwin 1998). In only one study of older adults in Berlin, Fiori and colleagues (2007) found that individuals belonging to a friend-focused supported network type (mostly unmarried with a high levels of contact with friends and average levels of instrumental and emotional support) had higher levels of depressive symptoms and morbidity and lower subjective well-being when compared with many of the other network types. The inconsistent findings regarding the health benefits of friend-oriented networks may be due to differences in how social network types are constructed or measured. While many of the previous studies examined frequency of contact with friends, perceived friendship quality or perceived social support, the network types used in this dissertation were derived purely from data on respondent reports of close confidants. Networks were characterized as friendship-oriented only if the respondent named solely friends (1 or more) as close confidants. Parents, children and siblings provide more financial aid, emotional support and instrumental support than friends, especially when a person’s needs are significant and chronic (Wellman and Wortley 1990; Adams and Blieszner 1995), while friendship provides companionship and leisure. It is possible that the mere presence of friendship, in the absence of other kin relationships, is deleterious to health. Older adults may not want to burden or overwhelm their friends with their own personal needs due to the voluntary, more delicate status of friendship.

The “Male-Focused” social network type was associated with all three indicators of well-being, predicting better self-rated health, higher self-esteem and fewer depressive symptoms. Why are networks composed entirely of men beneficial for both mental and physical health? Unfortunately, very few studies examine the different types of support provided by female and male social ties and the few studies available tend to focus on specific groups (e.g., male and female caregivers). It is possible that men and women provide different forms of support to their network members. This finding merits further study in future research.

The strong associations between network types and well-being could be due either to social causation or selection processes. Indeed, do particular network structures and compositions really promote health? Or does health status impact the extent to which individuals can attract and maintain social ties, resulting in changes in network structure and composition over time? To test hypotheses derived from a social causation explanation, I used network types (as measured at baseline) to predict well-being 3 and 8 years later. Again, social network typologies were better predictors of future mental health than of future physical health. In addition, the network composition types were predictors of self-esteem both 3 and 8 years after the initial survey, but only predicted psychological distress up to 3 years after the initial survey. Network structure types were not significant predictors of physical or mental health at either time point after the initial survey.

Lastly, structural equation modeling was used to simultaneously test social causation and selection hypotheses for self-rated health, psychological distress and self-esteem. Social causation and selection played a role in the relationships between network structure and self-rated health and psychological distress. For self-rated health, the standardized parameter estimate representing the social selection hypothesis (i.e., the effect of self-rated health at T1 on network structure at T2) was greater in magnitude and had a smaller p-value than the standardized parameter estimate representing the social causation hypothesis (i.e., the effect of network structure at T1 on self-rated health at T2). Thus, while both social causation and selection processes were at work, it appears that social selection plays a greater role in the relationship between self-rated health and network structure. Individuals' network structure may change due to changes in physical health status, making it difficult to attract new social ties or maintain existing ones. In addition, individuals with poor physical health may have increasingly smaller social networks due to social rejection by others or social withdrawal from existing social ties.

For psychological distress, the standardized parameter estimate for the social selection hypothesis (i.e., representing the influence of psychological distress at T1 on network structure at T2) was greater in magnitude and statistical significance than the standardized parameter estimate for the social causation hypothesis (i.e., representing the influence of network structure at T1 on psychological distress at T2). While both social causation and selection play a role in the connection between social networks and mental health, social selection appears to have a larger effect. Individuals with smaller, less dense network structure may suffer from poor mental health over time, perhaps due to a lack of social support or other resources. Additionally, those who suffer from high levels of psychological distress may find that it difficult to initiate social contact with potentially new or existing ties. Social rejection and social withdrawal may be two additional mechanisms that help to explain this selection effect. Additional support for the social causation hypothesis is seen in the parameter estimate for the effect of network change (between Time 1 and 2) on psychological distress at Time 2, whereby individuals undergoing a change in their closest confidant across time report higher levels of psychological distress later on.

For self-esteem, the findings provide some support for social selection, where individuals with high levels of self-esteem at Time 1 report belonging to larger, denser networks at Time 2. The findings for social causation are weak, at best. In earlier analyses, social network composition had a strong, consistent effect on self-esteem, both in cross-sectional analyses and over 3-8 years after baseline, providing strong support for social causation. It could be that no effect was found using structural equation modeling because, due to data limitations, only network structure (not network composition) was modeled across time. If data on network composition was collected over two or more time points, it would have been possible to measure transitions in network composition and estimate its' effect on health over time. Using all available information that was consistently measured across the two waves of data, only the gender and relationship type of each respondent's closest confidant and a rough measure of change in closest confidant was used in the analysis.

This study has several limitations that deserve discussion. First, information on gender and relationship type was obtained for a maximum of three close confidants at baseline. This limits the current study because construction of network composition types incorporated only a fraction of information for respondents who reported that they had more than three close confidants. It is estimated that surveys should assess 5 to 10 network members to take account of most close confidants because the average number of close confidants ranges from 4 to 8 in a majority of cross-national studies (Antonucci and Akiyama 1995). Also, reports of close confidants may represent only the inner-most circle of social convoys. It is possible that network members in outer circles are also important for health and well-being.

Second, this study was not able to identify the mechanisms by which social network structure and composition influence health. It is important to ascertain *how* social networks affect health and well-being. Do social networks have both direct and indirect effects on health? What are the important mediators in the networks-health connection? Scholars propose that social networks indirectly influence well-being through a number of potential pathways, including through the provision of emotional, instrumental, and informational social support, access to material resources, social influence, social control, social engagement and attachment (Umberson et al. 2010; Berkman and Glass 2000). Relatively recent research provides evidence for the mediating role of social support in the relationship of social networks to well-being. Lin, Ye and Ensel (1999) and Fiori, Antonucci and Cortina (2006) found that the effects of social convoys on mental health were partially mediated by social support. It is also possible that social networks may be beneficial in and of themselves, with effects on mental and physical health that are independent of social support or other proposed mechanisms. These findings are in line with those of Blazer (1982), who found that social ties and perceived social support independently predicted mortality among an elderly sample in the southern U.S. These findings highlight the importance of treating network structure and function as distinct concepts (House et al. 1985). This dissertation does not address *how* social networks influence health due to limitations of the data. Social networks were measured by respondent reports of close confidants. The ACL contains questions measuring the social support provided by certain kin relationships, such as by a spouse, mother, father or children, and uses only one question to measure the amount of social support provided by friends and other relatives in general. These sources of social support may not match up with the close confidants named by the respondent. For example, while a respondent may have a spouse, living mother, living father and children, he or she may report that their closest confidants are non-kin, such as friends, neighbors or co-workers. Thus, potentially important mechanisms for the social network – health connection could not be tested. Future research should assess important attributes of the network, including size, density and reciprocity, and important demographic information for each of the respondents' close confidants (e.g., age, gender, race, education, relationship types, etc.), in addition to perceived and/or levels of different types of social support provided by each named confidant. This information can then be used to assess potential mechanisms in for the relationship between networks health.

Lastly, only network structure could be modeled within the structural equation models presented in Chapter 3. The American Changing Lives Survey collected information on the gender and relationship type of respondents' three closest confidant in Wave 1, but then greatly shortened this section of the survey in the subsequent data collection periods. Wave 2 only collects information on the gender and relationship type of respondents' first closest confidant, while Wave 3 is even more restricted. Wave 3 collects information on the gender and relationship type of respondents' first close confidant, but fails to collect information on network density or number of instrumentally helpful network ties. This limited the options in regards to the type of data analysis performed (autoregressive cross-lagged models as opposed to dual trajectory models) and the variables incorporated into each analysis. Thus, while social network composition at baseline and a rough measure of change in the *closest* confidant were incorporated into SEM models, I could not model change in network composition over time.

Despite these limitations, this dissertation has many strengths. This is the only study to date that has: (a) used respondent reports of close confidants to measure network typologies; (b) developed separate typologies for social network structure and composition; (c) ascertained the extent to which structure and composition affect multiple dimensions of health, including physical health, negative and positive mental health; and (d) tested hypotheses about reciprocal relationships between networks and health due to social causation and selection. Future research endeavors will focus on testing potential mediators in the social network – health connection, such as emotional, instrumental and informational support, access to material resources, and social control. The National Social Life, Health and Aging Project (NSHAP), sponsored by NORC, has the potential for addressing these research goals among a national sample of older adults. While the first wave of data is publicly available through ICPSR, the second wave of data has recently been collected and will be publicly available soon. In addition, while much research has examined the cross-sectional associations between social networks and health, future research would benefit by examining the associations between trajectories of social network and trajectories of health.

Appendix A: Regression of Poor Self-Rated Health, Depressive Symptom Count and Life Satisfaction on Social Network Variables, ACL 1986 (N = 3,577), Weighted.

	POOR SRH	**DEP**	**HIGH SE**
Background Factors:			
Age	0.028***	-0.007***	0.015***
Female	-0.076	0.053†	-0.333**
Black	0.137	0.062*	0.262†
Married	0.365**	-0.075*	-0.303**
Children (Total #)	0.066*	0.009	0.006
High School	-0.512***	-0.143***	-0.005
> High School	-0.395**	-0.158***	0.321*
Income (Logged)	-0.687***	-0.119***	0.429***
Network Structure [1]			
Small	0.000	-0.059†	0.052
Mixed	-0.068	-0.242***	0.589***
Large	-0.008	-0.230***	0.719***
Network Composition [2]			
Diverse	-0.036	-0.120**	0.588***
Female Family	-0.086	-0.086†	0.256
Family + Spouse	-0.353†	-0.182***	0.623***
Female Spouse	-0.078	-0.344***	0.669***
Female Friends	-0.006	-0.038	0.165
Male-Focused	-0.398†	-0.183***	0.598***
Intercept	3.584	3.194	-3.820
AIC	2645.98	17639.17	3126.8
-2 Log Likelihood (BIC)	2609.98	(17756.64)	3090.8

*** $p < 0.001$ ** $p < 0.01$ * $p < 0.05$ † $p < 0.10$

Notes: [1] Reference group is 'Small, Not Dense'; [2] Reference group is 'Restricted'.

Appendix B: Logistic Regression of Poor Self-Rated Health on Social Network Typologies, ACL 1986 (N = 3577), Not Weighted.

	I	II	III	IV
Background Factors:				
Age	0.023***	0.023***	0.023***	0.023***
Female	-0.020	-0.025	-0.079	-0.083
Black	0.179†	0.167†	0.168†	0.157
Married	0.188†	0.193†	0.245*	0.248*
Children (Total #)	0.029	0.030	0.031	0.031
High School	-0.618***	-0.621***	-0.620***	-0.623***
> High School	-0.513***	-0.522***	-0.504***	-0.511***
Income (Logged)	-0.599***	-0.594***	-0.600***	-0.595***
Network Structure				
Small		-0.059	--	-0.017
Mixed		-0.245†	--	-0.201
Large		-0.045	--	0.025
Network Composition				
Diverse			-0.225	-0.226
Female Family			-0.162	-0.154
Family + Spouse			-0.276†	-0.282†
Female Spouse			-0.428*	-0.423†
Female Friends			-0.122	-0.118
Male-Focused			-0.396*	-0.386*
Intercept	3.117	3.165	3.347	3.363
AIC	3239.33	3241.56	3243.77	3246.34
-2 Log Likelihood	3221.33	3217.56	3213.77	3210.34

*** $p < 0.001$ ** $p < 0.01$ * $p < 0.05$ † $p < 0.10$

Notes: [1] Reference group is 'Small, Not Dense'; [2] Reference group is 'Restricted'.

Appendix C: Logistic Regression of Poor Self-Rated Health on Social Network Typologies, ACL 1986 (N = 3577), Weighted.

	I	II	III	IV
Background Factors:				
Age	0.028***	0.028***	0.028***	0.028***
Female	-0.065	-0.068	-0.075	-0.076
Black	0.155	0.151	0.141	0.137
Married	0.307*	0.312*	0.363**	0.365**
Children (Total #)	0.064*	0.064*	0.066*	0.066*
High School	-0.513***	-0.515***	-0.510***	-0.512***
> High School	-0.400**	-0.402**	-0.393**	-0.395**
Income (Logged)	-0.673***	-0.672***	-0.688***	-0.687***
Network Structure				
Small		-0.059	--	0.000
Mixed		-0.111	--	-0.068
Large		-0.087	--	-0.008
Network Composition				
Diverse			-0.037	-0.036
Female Family			-0.089	-0.086
Family + Spouse			-0.353†	-0.353†
Female Spouse			-0.080	-0.078
Female Friends			-0.009	-0.006
Male-Focused			-0.399*	-0.398*
Intercept	3.366	3.417	3.569	3.584
AIC	2636.97	2642.43	2640.31	2645.98
-2 Log Likelihood	2618.97	2618.43	2610.31	2609.98

*** $p < 0.001$ ** $p < 0.01$ * $p < 0.05$ † $p < 0.10$

Notes: [1] Reference group is 'Small, Not Dense'; [2] Reference group is 'Restricted'.

Appendix D: Negative Binomial Regression of Depressive Symptom Count on Social Network Variables, ACL 1986 (N = 3577), Not Weighted.

	I	II	III	IV
Background Factors:				
Age	-0.008***	-0.007***	-0.008***	-0.008***
Female	0.114***	0.102***	0.069*	0.054†
Black	0.082**	0.065*	0.076*	0.060*
Married	-0.126***	-0.120***	-0.085**	-0.082*
Children (Total #)	0.000	0.002	0.000	0.002
High School	-0.150***	-0.151***	-0.151***	-0.151***
> High School	-0.170***	-0.168***	-0.163***	-0.164***
Income (Logged)	-0.120***	-0.117***	-0.120***	-0.117***
Network Structure				
Small		-0.074*	--	-0.045
Mixed		-0.248***	--	-0.220***
Large		-0.229***	--	-0.190***
Network Composition				
Diverse			-0.177***	-0.129**
Female Family			-0.152**	-0.114*
Family + Spouse			-0.221***	-0.167**
Female Spouse			-0.367***	-0.351***
Female Friends			-0.050	-0.032
Male-Focused			-0.182***	-0.159**
Intercept	2.988	3.075	3.153	3.192
AIC	17197.47	17155.03	17165.36	17131.72
BIC	17259.29	17235.4	17264.28	17249.18

*** $p < 0.001$ ** $p < 0.01$ * $p < 0.05$ † $p < 0.10$

Notes: [1] Reference group is 'Small, Not Dense'; [2] Reference group is 'Restricted'

Appendix E: Negative Binomial Regression of Depressive Symptom Count on Social Network Variables, ACL 1986 (N = 3577), Weighted.

	I	II	III	IV
Background Factors:				
Age	-0.007***	-0.007***	-0.008***	-0.007***
Female	0.121***	0.108***	0.070*	0.053†
Black	0.087**	0.069*	0.080**	0.062*
Married	-0.125***	-0.118***	-0.079**	-0.075*
Children (Total #)	0.006	0.008	0.007	0.009
High School	-0.143***	-0.143***	-0.142***	-0.143***
> High School	-0.167***	-0.165***	-0.157***	-0.158***
Income (Logged)	-0.123***	-0.118***	-0.123***	-0.119***
Network Structure				
Small		-0.088**	--	-0.059†
Mixed		-0.268***	--	-0.242***
Large		-0.264***	--	-0.230***
Network Composition				
Diverse			-0.176***	-0.120**
Female Family			-0.130**	-0.086†
Family + Spouse			-0.245***	-0.182***
Female Spouse			-0.363***	-0.344***
Female Friends			-0.060	-0.038
Male-Focused			-0.210***	-0.183***
Intercept	2.980	3.077	3.149	3.194
AIC	17745.51	17675.75	17697.13	17639.17
BIC	17807.33	17756.12	17796.05	17756.64

*** $p < 0.001$ ** $p < 0.01$ * $p < 0.05$ † $p < 0.10$

Notes: [1] Reference group is 'Small, Not Dense'; [2] Reference group is 'Restricted'.

Appendix F: Logistic Regression of High Self-Esteem on Social Network Variables, ACL 1986 (N = 3577), Not Weighted.

	I	II	III	IV
Background Factors:				
Age	0.017***	0.017***	0.018***	0.018***
Female	-0.325**	-0.298**	-0.237*	-0.202†
Black	0.162	0.205*	0.185†	0.224*
Married	-0.083	-0.099	-0.158	-0.171
Children (Total #)	0.008	0.002	0.007	0.002
High School	0.203†	0.193	0.197†	0.190
> High School	0.380**	0.358**	0.350**	0.337*
Income (Logged)	0.454***	0.446***	0.453***	0.446***
Network Structure				
Small		0.024	--	-0.035
Mixed		0.418**	--	0.357*
Large		0.646***	--	0.514**
Network Composition				
Diverse			0.454**	0.331*
Female Family			0.233	0.149
Family + Spouse			0.574***	0.433*
Female Spouse			0.556*	0.541*
Female Friends			0.031	-0.018
Male-Focused			0.381*	0.341†
Intercept	-3.683	-3.779	-4.020	-4.015
AIC	3234.25	3213.88	3226.03	3212.14
-2 Log Likelihood	3216.25	3189.88	3196.03	3176.14

*** $p < 0.001$ ** $p < 0.01$ * $p < 0.05$ † $p < 0.10$

Notes: [1] Reference group is 'Small, Not Dense'; [2] Reference group is 'Restricted'.

Appendix G: Logistic Regression of High Self-Esteem on Social Network Variables, ACL 1986 (N = 3577), Weighted.

	I	II	III	IV
Background Factors:				
Age	0.013***	0.013***	0.015***	0.015***
Female	-0.462***	-0.433***	-0.380***	-0.333**
Black	0.182	0.245†	0.205	0.262†
Married	-0.189†	-0.212†	-0.288*	-0.303**
Children (Total #)	0.010	0.006	0.010	0.006
High School	0.004	-0.006	0.001	-0.005
> High School	0.378**	0.352*	0.332*	0.321*
Income (Logged)	0.440***	0.432***	0.435***	0.429***
Network Structure				
Small		0.115	--	0.052
Mixed		0.657***	--	0.589***
Large		0.882***	--	0.719***
Network Composition				
Diverse			0.761***	0.588***
Female Family			0.381*	0.256
Family + Spouse			0.806***	0.623***
Female Spouse			0.713***	0.669***
Female Friends			0.234	0.165
Male-Focused			0.656***	0.598***
Intercept	-3.189	-3.432	-3.709	-3.820
AIC	3183.23	3139.7	3158.28	3126.8
-2 Log Likelihood	3165.23	3115.7	3128.28	3090.8

*** $p < 0.001$ ** $p < 0.01$ * $p < 0.05$ † $p < 0.10$

Notes: [1] Reference group is 'Small, Not Dense'; [2] Reference group is 'Restricted'.

Appendix H: Regression of Poor Self-Rated Health, Depressive Symptom Count and Life Satisfaction on Social Network Variables, ACL 1986 (N = 3577), Weighted.

	POOR SRH	DEP	HIGH SE
Background Factors:			
Age	0.031***	-0.007***	0.016***
Female	-0.048	0.096***	-0.383***
Black	0.165	0.050†	0.314*
Married	0.273*	-0.054†	-0.360**
Children (Total #)	0.068*	0.007	0.008
High School	-0.526***	-0.134***	-0.055
> High School	-0.432**	-0.153***	0.264†
Income (Logged)	-0.690***	-0.111***	0.406***
Network Structure			
Network Size (Help/Advise)	-0.024	-0.031***	0.070***
Network Size (Share Feelings)	-0.013	-0.025*	0.090*
Network Density	-0.060	-0.022*	-0.019
Network Composition			
Spouse Nom	0.374*	-0.105**	0.338*
Family Nom	0.011	0.011	-0.188
Friend Nom	0.349*	0.070*	-0.020
All Female Noms	-0.250	-0.094†	0.220
All Male Noms	-0.591*	-0.039	0.423†
Mixed Gender Noms	-0.429	-0.136*	0.309
Intercept	3.804	3.214	-3.721
AIC	2631.85	17604.71	3123.67
-2 Log Likelihood (BIC)	2595.85	(17722.17)	3087.67

*** $p < 0.001$ ** $p < 0.01$ * $p < 0.05$ † $p < 0.10$

Appendix I: Regression of Poor Self-Rated Health, Depressive Symptom Count and High Self-Esteem on Social Network Typologies by Age, ACL 1986 (N = 3577), Not Weighted.

	POOR/FAIR SRH		DEP		HIGH SELF-ESTEEM	
	< 60	60+	< 60	60+	< 60	60+
Background Factors:						
Age	0.044***	-0.001	-0.008***	0.001	0.009	0.001
Female	-0.021	-0.185	0.057	0.030	-0.206	-0.196
Black	0.215	0.064	0.069†	0.044	0.260†	0.207
Married	0.224	0.209	-0.094*	-0.038	-0.226	-0.159
Children (Total #)	0.074*	-0.020	0.019†	-0.007	0.015	0.007
High School	-0.703***	-0.575***	-0.121*	-0.180***	0.149	0.367†
> High School	-0.439*	-0.475**	-0.143**	-0.159**	0.475**	0.001
Income (Logged)	-0.674***	-0.615***	-0.117***	-0.122***	0.414***	0.553***
Network Structure						
Small	0.011	-0.034	-0.086†	0.034	0.169	-0.440†
Mixed	-0.022	-0.308	-0.281***	-0.110	0.555**	-0.041
Large	0.313	-0.143	-0.242***	-0.084	0.738**	0.066
Network Composition						
Diverse	-0.316	-0.153	-0.126*	-0.176*	0.576**	-0.043
Female Family	-0.293	-0.061	-0.128†	-0.107	0.390†	-0.066
Family + Spouse	-0.840**	0.005	-0.239**	-0.138†	0.721**	0.174
Female Spouse	-0.294	-0.582†	-0.357***	-0.369***	0.769**	0.291
Female Friends	-0.041	-0.119	-0.070	0.000	0.060	-0.035
Male-Focused	-0.467†	-0.342	-0.179*	-0.160*	0.547*	0.140
Intercept	3.087	5.408	3.226	2.566	-3.803	-3.213
AIC	1353.54	1890.62	9452.88	7690.58	1828.72	1388.89
-2 Log Likelihood (BIC)	1317.54	1854.62	(9558.67)	(7793.25)	1792.72	1352.89

*** p < 0.001 ** p < 0.01 * p < 0.05 † p < 0.10

Notes: [1] Reference group is 'Small, Not Dense'; [2] Reference group is 'Restricted'.

Appendix J: Regression of Poor Self-Rated Health, Depressive Symptom Count and High Self-Esteem on Social Network Typologies by Gender, ACL 1986 (N = 3577), Not Weighted.

	POOR/FAIR SRH		**DEP**		**HIGH SELF-ESTEEM**	
	Women	Men	Women	Men	Women	Men
Background Factors:						
Age	0.019***	0.031***	-0.008***	-0.007***	0.020***	0.013*
Black	0.190	0.099	0.070†	0.042	0.234†	0.189
Married	0.318*	0.010	-0.099*	-0.065	-0.179	-0.080
Children (Total #)	0.017	0.060	-0.003	0.013	-0.003	0.012
High School	-0.791***	-0.243	-0.165***	-0.131†	0.330*	-0.169
> High School	-0.673***	-0.164	-0.176***	-0.141*	0.406*	0.144
Income (Logged)	-0.549***	-0.708***	-0.103***	-0.148***	0.418***	0.516***
Network Structure						
Small	-0.003	0.030	-0.038	-0.054	-0.152	0.193
Mixed	-0.058	-0.421	-0.192***	-0.263***	0.092	0.905***
Large	0.123	-0.098	-0.165**	-0.217*	0.326	0.877**
Network Composition						
Diverse	-0.280	-0.174	-0.087	-0.198*	0.300	0.367
Female Family	-0.149	-0.366	-0.068	-0.320**	0.142	0.165
Family + Spouse	-0.316	-0.263	-0.068*	-0.214*	0.535*	0.224
Female Spouse	-9.295	-0.343	-1.334	-0.405***	9.802	0.493†
Female Friends	-0.119	-0.175	-0.005	-0.030	-0.078	0.272
Male-Focused	-0.357	-0.468	-0.128†	-0.218*	0.232	0.502†
Intercept	3.150	3.920	3.130	3.487	-3.963	-4.659
AIC	2148.57	1112.68	10875.38	6266.37	2174.19	1054.45
-2 Log Likelihood (BIC)	2114.57	1078.68	(10978.19)	(6360.02)	2140.19	1020.45

*** $p < 0.001$ ** $p < 0.01$ * $p < 0.05$ † $p < 0.10$

Notes: [1] Reference group is 'Small, Not Dense'; [2] Reference group is 'Restricted'.

Appendix K: Regression of Poor Self-Rated Health, Depressive Symptom Count and High Self-Esteem on Social Network Typologies by Race ACL 1986 (N = 3577), Not Weighted.

	POOR/FAIR SRH		DEP		HIGH SELF-ESTEEM	
	Black	Other	Black	Other	Black	Other
Background Factors:						
Age	0.020***	0.027***	-0.009***	-0.007***	0.019***	0.018***
Female	-0.093	-0.085	0.093†	0.028	-0.030	-0.288*
Married	0.020	0.413**	-0.094†	-0.070†	0.004	-0.251†
Children (Total #)	0.035	0.025	-0.008	0.008	0.025	-0.016
High School	-0.455*	-0.735***	-0.122*	-0.173***	0.303	0.133
> High School	-0.350	-0.595***	-0.167*	-0.170***	0.458†	0.289†
Income (Logged)	-0.490***	-0.671***	-0.106***	-0.126***	0.504***	0.416***
Network Structure						
Small	-0.034	0.006	-0.020	-0.054	0.104	-0.097
Mixed	-0.168	-0.211	-0.177*	-0.235***	0.288	0.385*
Large	0.053	0.035	-0.100	-0.219***	0.515	0.484*
Network Composition						
Diverse	-0.411	-0.100	-0.102	-0.141*	-0.079	0.554**
Female Family	-0.137	-0.170	-0.172*	-0.066	-0.203	0.381†
Family + Spouse	-0.332	-0.283	-0.132	-0.190**	0.384	0.538**
Female Spouse	-0.657	-0.331	-0.373**	-0.360***	0.708	0.590*
Female Friends	-0.017	-0.173	-0.033	-0.025	-0.478†	0.251
Male-Focused	-0.188	-0.525*	-0.035	-0.222***	-0.054	0.562**
Intercept	2.783	3.812	3.170	3.267	-4.479	-3.677
AIC	1257.32	2006.58	5803.48	11335.19	1112.86	2115.76
-2 Log Likelihood (BIC)	1223.32	1972.58	(5894.45)	(11439.44)	1078.86	2081.76

*** $p < 0.001$ ** $p < 0.01$ * $p < 0.05$ † $p < 0.10$

Notes: [1] Reference group is 'Small, Not Dense'; [2] Reference group is 'Restricted'.

Appendix L: Regression of Self-Rated Health, Psychological Distress and Self-Esteem on Social Network Variables, ACL 1986, 1989 and 1994, Weighted.

	Wave 2 (N = 2,812)			Wave 3 (N = 2,195) [3]		
	SRH	**DEP**	**SE**	**SRH**	**DEP**	**SE**
Background Factors:						
Age	-0.004***	-0.008*	0.000	-0.001	0.001	-0.009***
Female	-0.074*	0.041	-0.118†	-0.016	-0.090	-0.135†
Black	-0.022	0.452*	-0.020	-0.142*	0.887***	0.071
Married	-0.008	0.229	-0.175*	0.030	0.201	-0.112
Children (Total #)	-0.022†	0.037	-0.002	-0.001	0.009	-0.001
High School	0.161***	-0.492**	0.198*	0.178**	-0.704***	0.382***
> High School	0.151**	-0.573**	0.330***	0.170**	-0.993***	0.438***
Income (Logged)	0.051*	-0.460***	0.211***	0.093**	-0.391***	0.118*
Self-Rated Health (W1)	0.547***	--	--	0.497***	--	--
Psychological Distress (W1)	--	0.407***	--	--	0.412***	--
Self-Esteem (W1)	--	--	0.470***	--	--	0.386***
Network Structure [1]						
Small	0.027	-0.387*	-0.002	0.074	-0.321†	0.003
Mixed	0.036	-0.238	-0.061	0.020	-0.393*	0.089
Large	0.100†	-0.655**	0.019	0.065	-0.209	0.080
Network Composition [2]						
Diverse	-0.035	-0.293	0.277**	-0.074	-0.519*	0.341**
Female Family	-0.044	-0.065	0.357**	-0.144†	-0.221	0.294*
Family + Spouse	0.015	-0.538*	0.465***	-0.028	-0.360	0.267*
Female Spouse	-0.148*	-0.184	0.275*	-0.152†	-0.505†	0.297*
Female Friends	0.015	0.032	0.270*	-0.009	-0.570†	0.347*
Male-Focused	0.130*	-0.727**	0.206†	-0.083	-0.104	0.371**
Intercept	1.104	16.792	3.188	0.657	13.091	5.297
Adjusted R Square	0.395	0.286	0.304	0.291	0.279	0.239

*** $p < 0.001$ ** $p < 0.01$ * $p < 0.05$ † $p < 0.10$

Notes: [1] Reference category is “Small, Not Dense”; [2] Reference category is “Restricted”; [3]The weight variable for the third wave of data is missing for 165 respondents who participated in Wave 3. Thus, the sample size for this analysis using weights is only 2,195.

Appendix M: Regression of Change in Self-Rated Health, Psychological Distress and Self-Esteem on Social Network Variables, ACL 1986, 1989 and 1994, Not Weighted.

	Change from W1 to W2 (N = 2,812)			Change from W1 to W3 (N = 2,360)		
	ΔSRH	**ΔDEP**	**ΔSE**	**ΔSRH**	**ΔDEP**	**ΔSE**
Background Factors:						
Age	0.001	0.014**	-0.008***	0.004**	0.024***	-0.022***
Female	-0.075†	-0.125	-0.116	0.044	-0.374†	-0.099
Black	0.019	0.129	-0.215**	-0.033	0.493**	-0.247**
Married	0.077†	0.476**	0.025	0.152**	0.640***	0.065
Children (Total #)	-0.008	0.038	-0.019	-0.005	-0.033	0.000
High School	-0.053	0.111	0.045	-0.058	-0.051	0.234*
> High School	-0.014	-0.011	0.117	-0.012	-0.396†	0.233*
Income (Logged)	-0.050†	-0.020	0.004	-0.051†	-0.162	-0.090
Network Structure [1]						
Small	0.010	0.098	-0.019	0.080	-0.002	-0.073
Mixed	-0.026	0.749***	-0.200†	0.007	0.177	-0.171
Large	0.083	0.415	-0.288*	0.149†	0.153	-0.225
Network Composition [2]						
Diverse	-0.110	0.162	0.118	-0.207**	0.001	0.033
Female Family	-0.101	-0.001	0.314*	-0.221**	0.036	0.200
Family + Spouse	-0.107	0.155	0.143	-0.223**	0.252	-0.149
Female Spouse	-0.224*	0.555	-0.009	-0.262**	0.190	-0.034
Female Friends	-0.049	0.198	0.177	-0.178*	-0.356	0.067
Male-Focused	0.037	-0.005	-0.019	-0.188*	0.572†	-0.048
Intercept	0.334	0.722	0.511	0.115	-0.434	2.130
Adjusted R Square	0.010	0.018	0.017	0.018	0.030	0.045

*** $p < 0.001$ ** $p < 0.01$ * $p < 0.05$ † $p < 0.10$

Notes: [1] Reference category is “Small, Not Dense”; [2] Reference category is “Restricted”.

Appendix N: Regression of Change in Self-Rated Health, Psychological Distress and Self-Esteem on Social Network Variables, ACL 1986, 1989 and 1994, Weighted.

	Change from W1 to W2 (N = 2,812)			Change from W1 to W3 (N = 2,195) [3]		
	ΔSRH	**ΔDEP**	**ΔSE**	**ΔSRH**	**ΔDEP**	**ΔSE**
Background Factors:						
Age	0.002†	0.013**	-0.007**	0.005**	0.028***	-0.017***
Female	-0.069†	-0.085	-0.087	0.003	-0.227	-0.093
Black	0.000	0.273	-0.261*	-0.091	0.607*	-0.169
Married	0.089*	0.423*	-0.078	0.147**	0.446*	-0.023
Children (Total #)	-0.017	-0.004	0.008	0.001	-0.059	0.021
High School	0.007	-0.055	0.155†	0.009	-0.371	0.343**
> High School	0.000	-0.042	0.213*	-0.008	-0.548*	0.309*
Income (Logged)	-0.059*	-0.027	-0.004	-0.017	0.020	-0.120*
Network Structure [1]						
Small	0.019	-0.089	-0.064	0.064	-0.063	-0.043
Mixed	0.008	0.616**	-0.274**	-0.013	0.415†	-0.137
Large	0.117†	0.064	-0.271*	0.096	0.567*	-0.287*
Network Composition [2]						
Diverse	-0.072	0.141	-0.007	-0.106	-0.133	0.085
Female Family	-0.107	0.089	0.218	-0.211*	-0.089	0.193
Family + Spouse	-0.093	0.151	0.069	-0.178*	0.307	-0.159
Female Spouse	-0.249***	0.724*	-0.113	-0.269**	0.299	-0.089
Female Friends	0.008	0.300	0.014	-0.028	-0.391	0.090
Male-Focused	0.075	-0.166	-0.104	-0.127	0.367	0.105
Intercept	0.327	1.123	0.611	-0.279	-2.307	2.119
Adjusted R Square	0.016	0.018	0.016	0.017	0.030	0.033

*** $p < 0.001$ ** $p < 0.01$ * $p < 0.05$ † $p < 0.10$

Notes: [1] Reference category is "Small, Not Dense"; [2] Reference category is "Restricted"; [3] The weight variable for the third wave of data is missing for 165 respondents who participated in Wave 3. Thus, the sample size for this analysis using weights is only 2,195.

Appendix O: Regression of Change in Self-Rated Health, Psychological Distress and Self-Esteem on Social Network Variables, ACL 1986, 1989 and 1994, Not Weighted.

	Change from W1 to W2 (N = 2,812)			Change from W1 to W3 (N = 2,360)		
	ΔSRH	**ΔDEP**	**ΔSE**	**ΔSRH**	**ΔDEP**	**ΔSE**
Background Factors:						
Age	0.001	0.012**	-0.008***	0.005**	0.022***	-0.021***
Female	-0.047	-0.250	-0.067	0.055	-0.418*	-0.060
Black	0.020	0.140	-0.222**	-0.027	0.488*	-0.214*
Married	0.074	0.556**	0.051	0.143*	0.640**	0.020
Children (Total #)	-0.008	0.035	-0.021	-0.004	-0.031	-0.001
High School	-0.053	0.096	0.050	-0.060	-0.046	0.227*
> High School	-0.016	-0.022	0.120	-0.017	-0.371	0.210†
Income (Logged)	-0.051†	-0.026	0.013	-0.053†	-0.159	-0.095
Network Structure						
Network Size (Help/Advise)	-0.005	0.081***	-0.024*	-0.002	0.018	-0.004
Network Size (Share Feelings)	0.027†	0.046	-0.042	0.018	0.051	-0.032
Network Density	-0.001	-0.016	-0.021	0.002	0.053	-0.066*
Network Composition						
Spouse Nom	-0.002	-0.264	-0.127	0.023	0.005	0.111
Family Nom	0.025	-0.279	0.093	-0.004	0.064	0.110
Friend Nom	0.033	-0.342	-0.014	0.035	-0.308	0.141
All Female Noms	-0.184*	0.437	0.262	-0.259**	-0.043	0.020
All Male Noms	-0.020	0.223	0.067	-0.224*	0.588	-0.115
Mixed Gender Noms	-0.208*	0.446	0.262	-0.269*	0.026	-0.137
Intercept	0.351	0.745	0.520	0.164	-0.581	2.263
Adjusted R Square	0.010	0.018	0.017	0.016	0.031	0.046

*** p < 0.001 ** p < 0.01 * p < 0.05 † p < 0.10

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Biography

Wendy Brynildsen Young was born in East Northport, NY in December 1982. She graduated with highest honors from Rutgers University in New Brunswick in May 2005. She received her Master of Public Health (MPH) degree, with a special concentration in epidemiology, from The University of Medicine and Dentistry of New Jersey in December 2006. She also earned a Master degree in Sociology from Duke University in September 2009. She currently lives in Apex, North Carolina with her husband and they are both anxiously anticipating the arrival of new member of their family in August 2013.

Her areas of specialty include aging and the life course, social gerontology, social networks and research methods. The focus of her dissertation, as well as current works in progress, apply network concepts and tools to the measurement of social relationships and networks from large-scale, observational surveys. Additional research projects have studied trajectories of romantic and sexual behaviors among emerging adults with S. Phillip Morgan and Suzanne Shanahan, as well as social networks and popularity trajectories among middle and high school students with James W. Moody.

Wendy has three co-authored peer-reviewed articles: (1) “Popularity Trajectories and Substance Use in Early Adolescence” with James. W. Moody, Wayne Osgood, Mark Feinberg and Scott Gest in *Social Networks;* (2) “Patient Weighting of Osteoporosis Medication Attributes Across Racial and Ethnic Groups: A study of Osteoporosis Medication Preferences using Conjoint Analysis” with Dr. Stuart Silverman, Andrew

Caleron, K. Kaw, Trenita Childers, B. Stafford, A. Focil, M. Koenig and Deborah Gold in *Osteoporosis International;* and (3) "The Influence of Meaning-Making after Spousal Loss on Trajectories of Psychological Distress" with Steven. L. Foy in *Society and Mental Health*. She also has a coauthored chapter entitled "Measuring Stress Outcomes" with Steven L. Foy and Linda K. George in <u>Blackwell Encyclopedia of Sociology</u>.

Wendy was generously supported in her research endeavors during 2009 – 2012 by an NIH T32 Traineeship in Social, Economic and Medical Demographic of Aging. She received an award from the Leadership in an Aging Society program during the summer of 2008. In addition, she received a Research Summer Fellowship through Duke Graduate School during the summer of 2012 and the Philip Jackson Baugh Graduate School Endowed Fellowship for 2012 – 2013.